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# INTELLECTUAL DIAGNOSTICS OF LINEARLY DISTRIBUTED OBJECTS USING WIRELESS SENSOR NETWORKS

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*Intellectual diagnostics of linearly distributed objects using wireless sensor networks is proposed. The solution of the task of functional diagnostics is realized by the expert system on the basis of the knowledge base in the form of a neuron-fuzzy network. For a technical object the current values of the diagnostic parameters are measured by wireless sensors. As an example, an expert diagnostic system for assessing the operability of a technical object.*

**1. Analysis of subject areas.** One of the most important tasks to ensure the required level of reliability and safety of complex technical objects is monitoring their current state. In this case, it is necessary to implement the collection, accumulation, processing and analysis of data from spatially distributed sensors in order to detect deviations of controlled parameters from the required value. Observation of a change in the situation allows a timely decision on the possibility of further exploitation of the facility. For complex distributed objects, it is advisable to use wireless sensor networks (WSN), which help you not only measure the values of the monitored parameter (passive sensors), but also manage the processes in objects using active sensors (activators). The lack of wires makes it possible to use the WSN in hard-to-reach places or on mobile objects, which greatly expands the range of sensor networks [1].

Many of the application areas of the WSN are related to the positioning of sensors in the form of a linear structure, which leads to the emergence of a new type of WSN, which can be defined as linear sensor networks LWSN. Such structures include railways, pipelines for oil, gas, water, etc. objects that can have a length of hundreds or even thousands of kilometers. The use of LWSN for monitoring tasks has some features that are related to a linearly distributed structure and a significant length of the network. In particular, such networks require considerable time for serial data transmission, have high power consumption while reducing the reliability of the transmission of information [2].

To eliminate the above disadvantages, LWSN and unmanned aerial vehicles (UAVs) are used to monitor

linear infrastructures that collect and transmit data. At the same time, the end-to-end transmission of data in the network is reduced, its reliability and fault tolerance are increased, the service life of the sensor batteries increases, the required quality of service is provided.

Structurally, the monitoring system has four types of nodes: sensors for collecting information (SN), relay nodes (RNs), UAVs and data receivers. SN nodes use the classic routing method to transfer their data to the nearest RN, which acts as a cluster gateway for surrounding SNs. The UAV moves sequentially along a reciprocating trajectory along a linear network and transmits the data that is collected by the RN to receivers located at both ends of the LWSN [3].

The use of UAV implements the advantages of the linearity of such networks to increase reliability, efficiency, energy savings and network lifetime [3].

Figure 1 shows the architecture of the monitoring system for LWSN. This system architecture has three levels. Wireless ground and underground sensors represent the bottom layer of the architecture, which provides the highest degree of detail for monitoring. At the second level, multimedia means and sensors increase the accuracy of the system by collecting visual information. At the third level, mobile terrestrial robots and UAVs represent the highest level of information gathering and provide the necessary completeness of diagnosis [4].

The communication between the RN nodes and the receivers is provided by the UAV, which moves between the receivers and collects the necessary data from the RN. The UAV board computer can also perform other functions such as data aggregation, scheduling, route, touch operating system and software configuration, programming, updating, and synchronizing SN and RN nodes. The UAV can be used to transport data and programs from receivers to SN, and may also have GPS capabilities. Since the through delay for transmitted data depends on the network structure and the UAV route, the on-board computer can analyze various options for reducing this parameter [4].

The main amount of information in the monitoring system is present in the first lower layer and with a large number of sensors there is a problem large data processing (Big Data). At the same time, the promising direction in the process of creating intelligent systems of functional diagnosis is the use of hybrid neural networks, which combine the advantages of fuzzy expert systems and neural networks. False logic in the development of the knowledge base (KB) and the mechanisms of output allows to formalize a procedure for assessing the technical condition on the basis of unreliable and inaccurate information when identifying possible malfunctions [5]. For the formation of logical conclusions in the intelligent diagnostic system (IDS), knowledge is used in the form of fuzzy function with linguistic variables that are represented by terms with some membership function (MF). In the presence of automated technical means for storing and collecting information from sensors of the object of diagnosis (OD) there is an opportunity to automate the replenishment of the KB and track the huge volumes of changing information, to take quality and timely solutions when diagnosing complex technical objects [6].

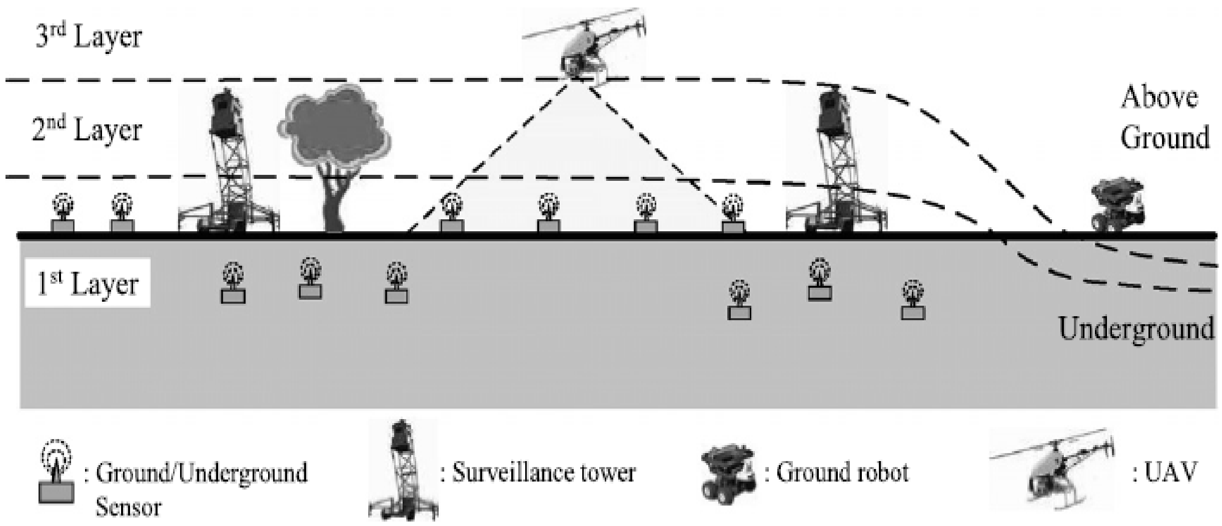


Figure 1 – Monitoring system for linearly distributed objects

**2. Setting the task.** The main purpose of this work is the development of automated methods for intelligent functional diagnosis with the use of measuring wireless sensors in the monitoring system of complex linearly distributed technical objects.

In the process of achieving the main goal, the following tasks are formulated and solved:

– conducting a continuous analysis of the technical state of the OD in the process of functioning without disturbing functional links;

– operational receipt of information about the technical state of the OD at an arbitrary time;

– the elimination of the need for additional stimulus signals for OD in the diagnostic process;

– the possibility of predicting deviations of the technical state of the OD from normal in the process of obtaining current data from sensors.

Information part of IDS provides accumulation, storage and transfer of information to other parts of it, and also implements the interface of the end user. Data from sensors is unstructured and requires further processing. The need for real-time decision-making results in the fact that the number of decision trees constructed according to incoming data should be equal to the number of counts (analogue of conveyor data processing). Tree decision trees for each time interval require significant memory costs for the IDS, so averaging for input data is usually used to reduce such costs. However, information on current changes in data from sensors over a period of time may be lost, which is a significant disadvantage of the methods for calculating averages. The problem of a significant amount of complex OD data can be solved by using these data as a training sample for neuro-fuzzy KB.

The IDS considered in this paper, along with the use of traditional knowledge, allows us to use the neural networks and to formalize the above practical problems that arise during the operation of various technical objects to achieve the main goal of work.

**3. Neuro-fuzzy knowledge database in the system of intellectual diagnosis.** The use of IDSs with neuro-fuzzy KB to solve problems of diagnosing complex technical objects extends the capabilities of such a class of intellectual systems, allows for an expert estimation of more variants, with increasing the reliability and accuracy of the obtained results, with equal computational resources.

The main problem with the creation of ISD is the development of the neural network structure for the implementation of a neuro-fuzzy KB. The structure of the neural network is similar to that of a regular multi-layer neural network with one input layer, one output layer and three hidden layers. An example of a possible neural network structure is given in [5].

The algorithm for functional diagnosis consists in comparing the mathematical model of a concrete diagnostic object with its reference and defect-free model, i.e. in checking the belonging of the status parameters to the permissible range of their change. Output of a parameter beyond these ranges should indicate that there is a malfunction in the corresponding subsystem of the object. In the hybrid neural network, the reference model of the OD is stored in the KB and specified in the process of acquiring new knowledge. The real model is formed in the database environment, and communication with the reference model is carried out through user requests. The solution of the problem of constructing an intelligent system of technical diagnostics of the state of the OD based on the hybrid ISD is made taking into account the features of the external environment conditions and the specifics of the adaptation of the model in this environment.

The peculiarity of modern ODs for processing information and management is that the diagnostic result depends on the number of input diagnostic parameters (DPs) and the corresponding linguistic variables (LV). The initial data at this stage is a list of all possible inputs (diagnostic features), on which the output (diagnostic result) depends. Too much of them will lead to complication of the diagnostic algorithm, so it is advisable to use only the transmission of information to other parts of it, and implements the end-user interface. Incoming data from the sensors is an unstructured form and requires further processing.

The need to take decisions in real time results in that the number of trees constructed in accordance with the incoming data must be equal to the number of counts (pipelined analog data). Storage of decision trees for every time interval requires considerable memory consumption IDS, so the averaging is typically used for the input data to reduce such costs. However, this information may be lost on the current data from the sensors changes over a period of time, which is a significant lack of methods for calculating averages. The problem of large amounts of data (Big Data) isolating the complex can be solved by the use of these data as atraining sample for neuro-fuzzy knowledge base. Considered in this paper, IDS, along with the use of traditional knowledge, it allows the use of neuro-fuzzy network knowledge base and formalize practical problems arising in the operation of electronic equipment listed above, in order to achieve the main goal of the work.

The use of hybrid neuro-fuzzy knowledge base with IDS to meet the challenges of diagnosing complex technical objects extends the capabilities of this class of intelligent systems, allowing for equal computing resources to carry out peer review more options, increasing the reliability and accuracy of the results.

The main problem in creating IDS is the development of neural network structure to implement neuro-fuzzy knowledge base. This issue is devoted to a lot of scientific publications, which shows the different structures of neural networks for solving the problem, for example [5]. The structure of the neuro-fuzzy network is similar to the structure of a conventional multi-layer neural network with one input layer, one output layer and three hidden layers. Consider the example of a possible structure of the neuro-fuzzy network (Fig. 2).

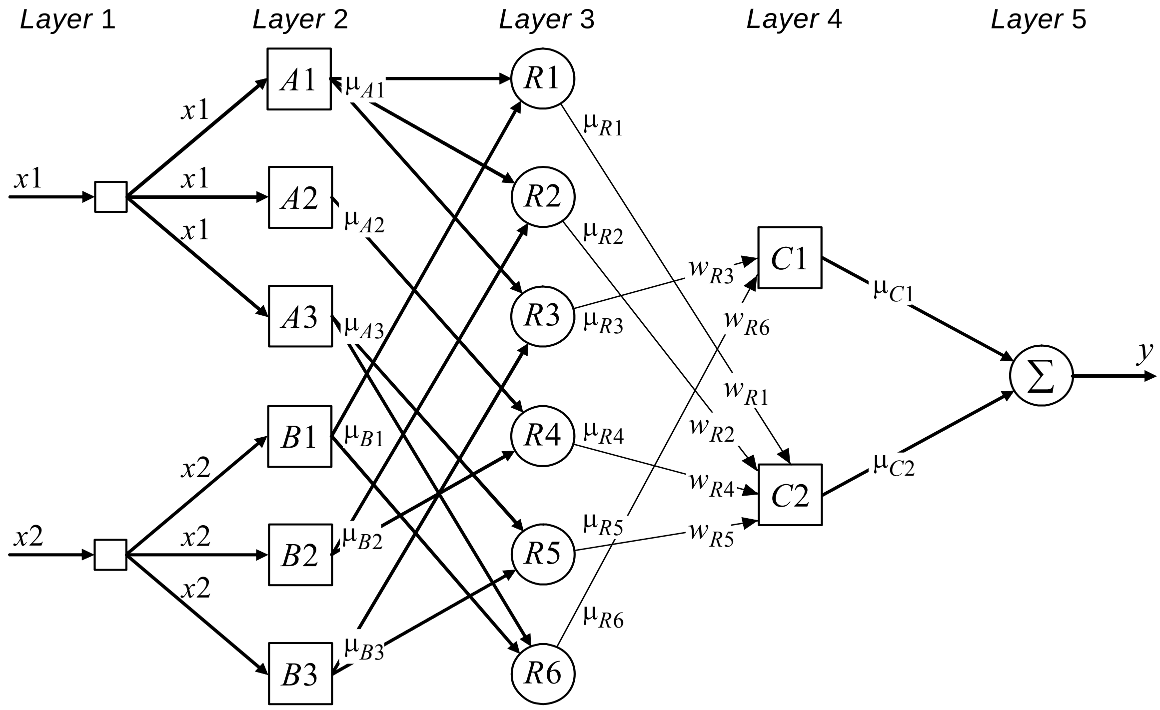


Figure 2 – Structure of the neuro-fuzzy network

For this example, neuro-fuzzy network has two inputs - X1, X2 and single output Y. X1 is represented by fuzzy sets A1, A2 and A3; Input X2 - sets B1, B2 and B3; Output Y - sets C1 and C2.

Each layer of the network in Figure 2 corresponds to one step of the fuzzy inference process for the production rules R1, ..., R6.

1. Layer 1. In terms of the first layer set of input variables. Each node of the first layer is a term with a triangular membership function. In this layer are calculated values of the coefficient accessories in accordance with the applicable fuzzification function for each of the six production inference rules.

2. The layer 2 determined antecedents (premises) of fuzzy rules. The output node is the degree of compliance with the rules, which is calculated as the product of the input signals.

3. Layer 3 is the fuzzy rule layer. Each neuron in this layer corresponds to a single fuzzy rule. A fuzzy rule neuron receives inputs from the fuzzification neurons that represent fuzzy sets in the rule antecedents. For instance, neuron R1, which corresponds to Rule 1, receives inputs from neurons A1 and B1.

4. Layer 4 is the output membership layer. Neurons in this layer represent fuzzy sets used in the consequent of fuzzy rules. An output membership neuron receives inputs from the corresponding fuzzy rule neurons and combines them

5.Layer 5 is the defuzzification layer. Each neuron in this layer represents a single output of the neuro-fuzzy system. It takes the output fuzzy sets clipped by the respective integrated firing strengths and combines them into a single fuzzy set.

The output of the neuro-fuzzy system is crisp, and thus a combined output fuzzy set must be defuzzified. Neuro-fuzzy systems can apply standard defuzzi-fication methods, including the centroid technique. In our example, we will use the sum-product composition method which offers a computational shortcut for the Mamdani-style inference.

Functional diagnosis algorithm is to compare the mathematical model of a particular object being diagnosed with a defect-free, and its reference model, ie, in checking supplies status parameters are in the range of their changes. The output parameter outside these ranges must indicate the presence of a fault in the appropriate subsystem object. In a hybrid neuro-fuzzy reference model ISD stored in the KB and to be confirmed in the process of acquiring new knowledge. The real model is formed in the database environment, and the relationship with the reference model through user queries. The task of building an intelligent system of technical diagnostics OD state on the basis of hybrid IDS made taking into account features of the external environment and the specific adaptation of IDS protection models in a given environment.

**4. Application of the IDS for a object diagnosis.** Any modern computer system's information processing and management, regardless of the scope of its use, can be represented by a set of hardware, software and staff. Failures in hardware can lead to the generation of a false signal, which is fed to the input of software components. This can lead to the failure of the software. In such critical (emergency) situations the staff also often makes mistakes. The incorrect actions of the latter, in turn, can provoke failures and errors in the hardware or software. Thus, an error, occurring in a single component, can lead to the failure of the entire computer system [6].

Abstracting from the type of OD (whether hardware, software or human operator), the result of diagnosis is significantly affected by the number of input diagnostic parameters (DP) or the corresponding linguistic variables (LV). The initial data at this stage is a list of all possible inputs (diagnostic variables), on which the output (diagnosis result). Too large number of them will be more difficult diagnosis algorithm, so it is advisable to use only independent diagnostic features.

For an example of the functioning of the ISD, we believe that it is possible to measure numerical values for 24 diagnostic parameters (DP1, ..., DP24). The values of the sensor readings are obtained at discrete moments of time t0, t1, t2, ..., ti. The time interval (ti+1-ti) between two adjacent dimensions is selected taking into account the speed of the change of diagnostic parameters. All 24 characteristics will play the role of diagnostic parameters in the process of intellectual diagnosis.

Let us consider the membership function of the input variable DP2, which corresponds to the diagnostic indication " Temperature" (Fig. 3), and Table 1 contains its parameters.

The core of any system is the fuzzy output KB, based on production rules (PR). There is a fairly large number of methods of creation of PR by the informal drafting expert based his ideas on the OD, to heuristic algorithms and formal synthesis. In this example, a method has been used as proposed in [5].

Due to the despite the different ways of PR, they must satisfy the formal requirements of correctness, not related to their semantic aspect. Correct PR system should be complete, minimum, coherent and consistent. Full description of the PR base verification procedure for correctness given in [7]. Full volume received by BR in Fig. 4 is only fragment of the graphical representation of production rules (17 pcs.).

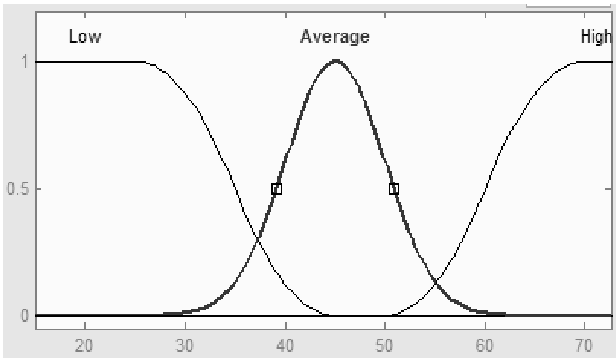


Figure 3 – Membership function

Table 1 – The values for a $DP_2$

| Terms of LV | Ranges of values | | Values membership |
|---|---|---|---|
| L (below normal) | 15 | 45 | a=25, b=45 |
| A (normal) | 35 | 55 | σ=5, M=45 |
| H (above normal) | 50 | 72.6 | a=50, b=70 |

The structure of the resulting neuro-fuzzy network is presented in Fig. 4. For this example, neuro-fuzzy network has 24 inputs - DP1, ... DP24 and one output (the result of the diagnosis, RD).

For this neuro-fuzzy network input vector entered diagnostic parameters [DP1, ... DP24]: [40 33 45 45 44 45 42 41 40 43 33 13.86 9.07 999 1129 1098 1020 1,188 3,344 5,042 11,926 1,044 1,524 0,963]. fuzzy inference system showed the following results: RD = 95.1%, which indicates that the PC is operational. This confirms the fact that all DP values lie within the normal range (Table. 1). If at least one parameter is higher than normal, the performance of the OD falls sharply. For example, the vector [40 72.6 45 45 44 45 42 41 40 43 33 13.86 9.07 999 1129 1098 1020 1,188 3,344 5,042 11,926 1,044 1,524 0,963] performance is at the level of 48.8%, which indicates a serious problem that can lead to the complete failure of the technical object.

6. Conclusions. In determining the technical condition of the complex technical facilities major critical factor is the time of the decision to localize faults. The use of hybrid expert diagnostic system with neuro-fuzzy network knowledge base provides support for decisions in situations for which the diagnosis algorithm is not known and is formed from the initial data in the form of production rules.

To automate the process of accumulation of knowledge in an expert system, it is advisable to use sensors of the technical object, by means of which measured values of diagnostic parameters.

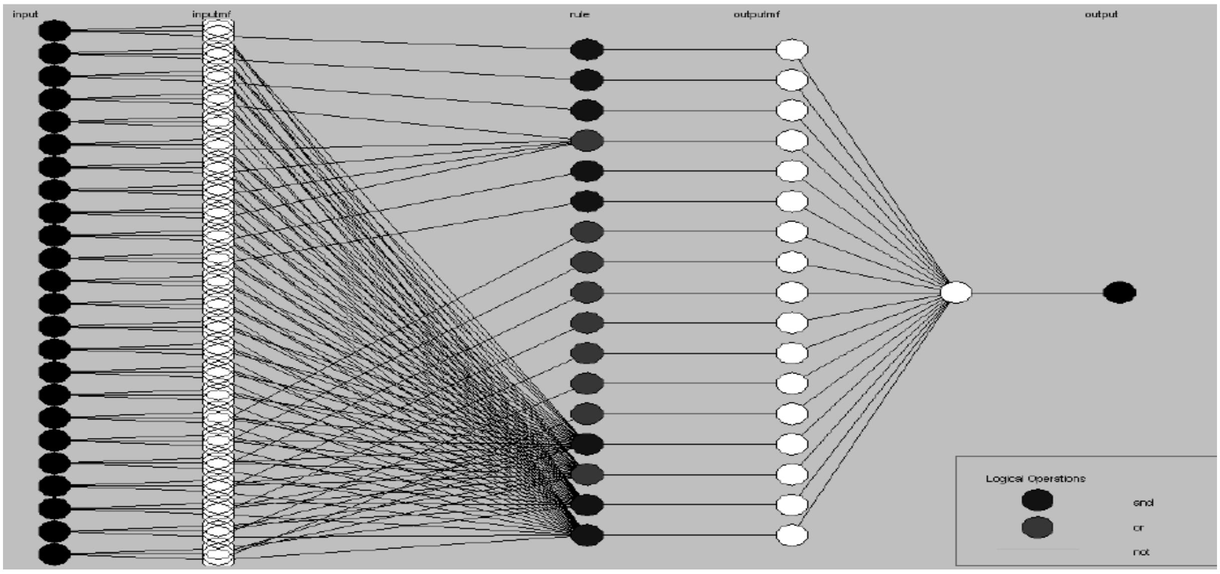


Figure 4 – Neuro-fuzzy network

The need to take decisions in real time results in that the number of trees corresponding to incoming data, equal to the number of samples during the observation period. The problem of large amounts of data in determining the technical condition of the complex technical object is solved by using this data as a training sample for neuro-fuzzy knowledge base.

## BIBLIOGRAPHY

1. Mosad H Alkhathami. Overview of Border Control Using Wireless Sensor Network. International Journal of Scientific & Engineering Research, Volume 6, Issue 3, March-2015, pp.768-772.

2. Jawhar N. Mohamed and D. P. Agrawal, "Linear Wireless Sensor. Networks: Classification Applications," in The Journal of Network and Computer Applications, Elsevier, Vol. 34, No. 5, pp. 1671-1682, Sept. 2011.

3. G. Tuna, T. V. Mumcu, K. Gulez, V. C. Gungor, and H. Erturk, "Unmanned aerial vehicle-aided wireless sensor network deployment system for post-disaster monitoring" in Emerging Intelligent Computing Technology and Applications. Springer, 2012, pp. 298–305.

4. Zhi Pu Wang.Mehmet C. Vuran.Mznah A. AI-Rodhaan,Ian F. Akyldiz. "BorderSense: Border patrol through advanced wireless sensor networks". Ad Hoc Network. № 9 , 2011, pp.468-477.

5. Krivoulya G. Expert diagnosis of computer systems using neuro-fuzzy knowledge base/ Krivoulya G., A. Lipchansky, Ye. Sheremet EWDTS'2014: Proceding. of international conference., 15-17 September, 2016. – Erevan. – P. 619-622

6. Krivoulya *G.* Expert evaluation model of the computer system diagnostic features / G. Krivoulya, A. Shkil, D. Kucherenko, A. Lipchansky, Ye. Sheremet // EWDTS'2014: Proceeding of international conf., 26-29 September, 2014. – Kiev, Ukraine,2014 – P. 286-289.

7. Krivoulya, G. Analysis of production rules in expert systems of diagnosis / G. F. Krivoulya, A. S. Shkil, D. Ye. Kucherenko // Automatic Control and Computer Sciences. – 2013. – Vol. 47. – №6. – P. 331-341.

**Аннотация**

### ИНТЕЛЛЕКТУАЛЬНОЕ ДИАГНОСТИРОВАНИ ЛИНЕЙНО РАСПРЕДЕЛЕННЫХ ОБЪЕКТОВ С ИСПОЛЬЗОВАНИЕМ БЕСПРОВОДНЫХ СЕНСОРНЫХ СЕТЕЙ

Кривуля Г. Ф., Обасикене Эммануэль Чуквунонсо, Власов В. А.

*Предложено интеллектуальное диагности-рование линейно распределенных объектов с использованием беспроводных сенсорных сетей. Решение задачи функционального диагностирования реализовано экспертной системой на основе базы знаний в виде нейронечеткой сети. Для технического объекта текущие значения диагностических параметров измеряются беспроводными сенсорами. В качестве примера рассмотрена экспертная система диагностирования для оценки работоспособности технического объекта.*

**Анотація**

### ІНТЕЛЕКТУАЛЬНЕ ДІАГНОСТУВАННЯ ЛІНІЙНО РОЗПОДІЛЕНИХ ОБ'ЄКТІВ З ВИКОРИСТАННЯМ БЕЗДРОТОВИХ СЕНСОРНИХ МЕРЕЖ

Кривуля Г. Ф., Обасікене Эммануель Чуквунонсо, Власов В. А.

*Запропоновано інтелектуальне діагностування лінійно розподілених об'єктів з використанням бездротових сенсорних мереж. Рішення завдання функціонального діагностування реалізовано експертної системою на основі бази знань у вигляді нейронечіткої мережі. Для технічного об'єкта поточні значення діагностичних параметрів вимірюються бездротовими сенсорами. Як приклад розглянута експертна система діагностування для оцінки працездатності технічного об'єкта.*