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THE CONCEPT OF A MODULAR CYBERPHYSICAL SYSTEM FOR THE EARLY DIAGNOSIS OF ENERGY EQUIPMENT

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Запропоновано концепцію модульної кіберфізичної системи для ранньої діагностики промислового та приватного енергетичного обладнання на основі використання підходів та стандартів Industry 4.0, зокрема концепції Internet of Things. Головною задачею запропонованої концепції та підходів є виконання непрямої діагностики та ідентифікації будь-якого енергетичного обладнання, головним елементом якого є асинхронний двигун, зокрема визначення несправностей та підвищеного енергоспоживання. З метою реалізації поставлених задач запропоновано використання модульної структури Smart Box діагностуючих пристроїв. Зокрема, представлено модель модульної кіберфізичної системи із застосуванням Smart Box прийстрою для ранньої технічної діагностики електрообладнання та його інформаційні потоки. Це дозволяє розподілювати усі технологічні об'єкти підприємства на окремі структурні одиниці, які можуть бути частиною інформаційного кластеру. Це дозволяє зменшити час реакції в кластерній системі на 30–35 %, у порівнянні зі звичайною. Також, використання даного типу системи дозволяє зменшити кількість спеціалізованого обладнання у межах використання однотипного енергетичного обладнання.

У якості обчислювального ядра Smart Box пристрою запропоновано використовувати структуру нейро-нечіткої мережі, яка складається з 5 шарів. Особливістю даної системи є можливість зміни кількості термів вхідних змінних з метою підвищення якості ідентифікації асинхронних двигунів. У якості інформативних ознак було обрано характерні частоти, які ідентифікують електродвигун у електромережі. Зокрема, у системах з малими генеруючими потужностями, з метою збільшення діагностованих асинхронних двигунів в межах кластеру, доцільно зменшити вхідну множину, наприклад, до 3–4 ХЧ.

Отримані результати дослідження у вигляді моделі модульної кіберфізичної системи можливо використовувати при побудові апаратно-програмних модулів для діагностики технологічного та побутового електрообладнання. У свою чергу, дані модулі можуть обє'єднуватися у загальну глобальну мережу IoT

Ключові слова: Smart Box, Industry 4.0, рання діагностика, кіберфізична система, асинхронний двигун

1. Introduction

At present, the main energy working units at modern enterprises are electric drives. In most cases, their principal elements are the multiphase induction motors (IM). This type of electric motors is quite common. This is evidenced by the fact that they consume about 40 % of all electricity produced in the world [1, 2]. The main feature of a given type of equipment is a high failure rate, in particular, the average operational lifecycle of motors without a major repair is 10–15 years. Failure to detect emergency modes of IM leads to the disruption of continuity of technological processes with the related damage to products, cost of restoration and repair of electric motors, elevated energy consumption, etc. Specifically, this issue is relevant for the ore mining and metallurgical industries where a sudden failure of electrical equipment can almost stop the large part of production lines [3, 4].

Modern tools and methods for technical diagnosis of electrical equipment is mainly based on the use of various sensors that are connected directly to the object (that is, direct methods). In particular, most of them are applied during a planned repair or current diagnosis [1, 5]. It should be noted that authors understand the concept of the planned diagnosis or maintenance as a partial or complete termination of the technological process, which involved the object of analysis. An early or current diagnosis, respectively, refers to the monitoring of the current state of the examined object that does not imply its immediate disengagement from the technological process. The main advantage of the current (early) technical diagnosis over the planned one is a relatively small period of time (up to a few seconds) to obtain results. In addition, early diagnosis makes it possible to prevent the emergency modes of industrial and household equipment. The use of modern information technologies to monitor and analyze the current technical condition of electrical equipment is an important and relevant task. That makes it possible to maintain and implement modern requirements regarding the implementation of processes of interaction, monitoring and analysis of operation of electrical units, pumps, mills, conveyors, robotic systems, etc.

In other words, meeting the requirements and future standards that are included in the concept of the fourth industrial revolution (Industry 4.0) [6–9].

It should be noted that modern electronic-information systems for enterprises enable the processes of automation and control over equipment. Additionally, they provide for the interconnection between integrated information subsystems and certain equipment, particularly microcontrollers, smart sensors, etc. [10, 11]. In addition, there is a growing tendency to manage, control and monitor industrial and household objects using the global network of the Internet of Things (IoT) as one of the promising areas of Industry 4.0 [12, 13]. In this case, the tools are combined based on the specialized centers that manage, control, and process information. According to data from Ericsson Mobility Report [15], at present, there are almost 16 billion devices connected to the Internet worldwide. Up to 2020, the number of such devices will increase to 29 billion, 18 billion of which will be connected to the network of IoT.

The main features of information systems that employ approaches and concepts of IoT include the process of permanent exchange of information between the devices at an enterprise without human involvement. This makes it possible to accumulate and analyze information under automatic mode, to execute administration without human influence. In other words, IoT enables the creation of a self-organized and self-adjustable information system, not only within the limits of a certain enterprise, but globally. That is, in terms of diagnosing and monitoring the current state of electrical equipment, it makes it possible to create and implement the information system capable of learning and self-diagnosis.

A relevant task for the further development of information systems for the analysis and monitoring of the status of electrical equipment is the development of self-diagnosing technical systems that would be a part of the global network of IoT. Specifically, the development of methods and approaches to creating the network elements, such as Smart Boxes and Smart Apps, the development of a network to access data (mobile or fixed), as well as development of a platform to manage the network of IoT, particularly when managing Smart Boxes and Smart Apps.

2. Literature review and problem statement

It should be noted that the creation of the network of IoT requires three key components:

1) Smart Box and Smart App;
2) a network to access data transfer and sharing;
3) a platform to manage the IoT elements.

To implement the network access to the IoT elements, the unified specialized standards are employed [6]. Specifically, the standard eMTC (enhanced Machine-Type Communication) is deployed based on the mobile networks LTE, while EC-GSM-IoT (Extended Coverage – GSM – Internet of Things) operates over a GSM network. But the most popular is the standard NB-IoT (Narrowband IoT). Its special feature implies that it can be deployed both in GSM or LTE networks and independently, as a separate network, such as Ethernet. Therefore, we can conclude that the design and development of SmartBox need to consider the unified specified-above communications standards for the implementation of the future platform for interaction between devices.

At present, many companies engaged in the manufacturing of energy equipment are conducting research into the field of innovation for IoT. Specifically, company LG has created a technology for intelligent self-diagnosis Smart Diagnosis and a control system for energy consumption Smart Grid Ready [16]. These technologies make it possible for the latest versions of household appliances made by this company to conduct the self-diagnosis and inform the user about it. Using Wi-Fi, NFC and sound diagnostic signals, the owner is given a notice about minor problems. For example, about switching an ice generator off or an emergency mode in the work of a washing machine's electric motor. It contributes to the early diagnosing of damage and improper operation of electric equipment. The main disadvantage of this system is the use of proprietary protocols and operation modes of "intelligent" devices, which makes it impossible to apply these devices for different equipment, such as a washing machine made by another company.

Quite a powerful information system for IoT in the field of diagnosing the electric equipment is the software platform Winnum [17]. A given system is the integrated environment that enables the collection, storage and processing of large volumes of data (BigData). This makes it possible to monitor the work of nodes in the system, in particular, monitor the status and technical conditions of electrical equipment. There is a possibility to restore the events that preceded the emergency mode. The main disadvantage of a given system is the limited range of supported power devices, particularly, only industrial machines with human-program management and the limited range of operating IM.

It should be noted that there are information technologies, procedures and hardware tools for the digital diagnosis of IM as a component of electrical equipment that uses the spectrum-current analysis of the electric grid. This method makes it possible to monitor IM without a direct connection to the examined object [1, 18]. The spectrum-current analysis most commonly employs a direct Fourier transform, in order to receive, for example, the amplitude-frequency characteristic in real time. The main disadvantages of information technologies that exploit the spectrum-current analysis include the use of a large number of sensors, the need for the presence of an expert to act as the final element who makes decisions on the technical condition of equipment.

Study [19] proposed the concept of information system as part of the intelligent enterprise and the network of IoT, which enables the exchange of information between the examined elements. That is, it makes it possible for the electric equipment to work and monitor at the same time the current technical condition of each other. The main disadvantages of a given approach include the presence of large amounts of non-deterministic information as a consequence of the technological process and the presence of a large number of additional sensors for each energy equipment item.

Thus, based on the scientific literature reviewed [6–19], we can conclude that the concept of the development of information self-diagnosing systems as parts of IoT is a promising direction. However, the main drawback is that almost all of the existing developments in a given direction are commercialized with the technologies themselves being closed and applied within a specific enterprise. That is, there is no a single unified and universal system that implements the commonly accepted methods and techniques for the technical diagnosis of electrical equipment. In addition, the general disadvantages include the fact it is required to use, when diagnosing the electrical equipment, measuring sensors for each studied object, which increases the overall cost of implementing this kind of systems at an enterprise. Moreover, in the case of implementing the IoT technology, there is no a single information platform to manage them at all.

In order to reduce the number of the pickups used, we propose an indirect technique for diagnosing the complex of IM, suggested in studies [1, 18], and which is based on a spectrum-current analysis of the electric grid. That would make it possible in the future to implement modular Smart Box devices as elements of the general IoT network. The result could enable the application of fewer diagnosing sensors and the implementation of a unified management platform for various modules included in the Smart Box.

3. Literature review and problem statement

The aim of this work is to develop a concept of the modular cyberphysical system for the early diagnosis of energy equipment based on the principles and standards of Industry 4.0, specifically IoT. The base method for diagnosing IM will be the indirect technique of diagnosis established in studies [1, 18].

To accomplish the aim, the following tasks have been set:

– to construct a logical-functional circuit for the operation of IoT network, which consists of modular Smart Box diagnosing devices, and to define the basic principles of its functioning;

– to design the structure of a modular diagnosing Smart Box device with existing external interfaces for integrating it into the general IoT system based on spectral analysis;

– to choose informative input attributes and the structure of a neural-fuzzy network as a unit of logical derivation and adaptation, which is the core of a diagnosing Smart Box device;

– to model, to run analyses for the feasibility and rationality of using the proposed concept of a modular cyberphysical system.

4. The concept of a modular cyberphysical system for the early diagnosis of power equipment

A typical logical-functional schematic of an enterprise that employs the principles of Industry 4.0, specifically IoT, is shown in Fig. 1.

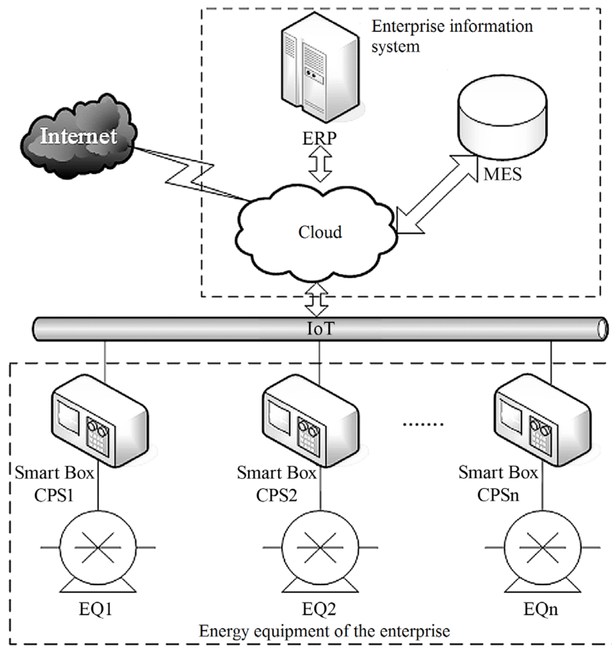

Fig. 1. Logical-functional schematic of an enterprise that employs the Smart Box diagnosing devices

In Fig. 1, ERP (Enterprise Resource Planning) is the integrated management of the basic business processes that is realized by software and the production technology. MES (Manufacturing Execution System) is the computerized systems that are used in the production, for monitoring and documenting the transformation of raw materials into finished products. Smart box is the software-hardware device that is used to read the current information from the investigated object, particularly the spectral characteristics of the equipment. This is executed by applying the sensors of current. EQ_1, EQ_2,..., EQ_n is the equipment from which current information is read. In this case, these are electric motors.

It should be noted that MES supplies information that helps manufacturers who make decisions understand the ways to optimize the current operational modes of equipment. In turn, that makes it possible to improve the performance efficiency of production based on the optimal operation with the minimization of costs for technical diagnosis and subsequent repair.

Thus, based on the shown logical-functional schematic (Fig. 1), the typical scheme of integration of the Smart Box device for the determining the technical condition of the examined object will take the following form (Fig. 2).

Fig. 2 shows: $A=\{a_1(f), a_2(f),..., a_m(f)\}$ is the spectrum of the electric grid noise; $I(t)$ is current; $J=\{j_1(t), j_2(t),..., j_n(t)\}$ are the higher harmonics created by the electrical equipment in the electric grid; x_c are the decisions concerning the current state of the electric motor; $\alpha(t)$ is the character of the workflow; $B=\{b_1(t), b_2(t)...b_n(t)\}$ are the higher harmonics created by other non-examined objects; $z(t)$ is the character of the electric motor loading; $\varphi(t)$ is the character of work of the non-examined objects; μ is the vector of parameters for setting a SmartBox device.

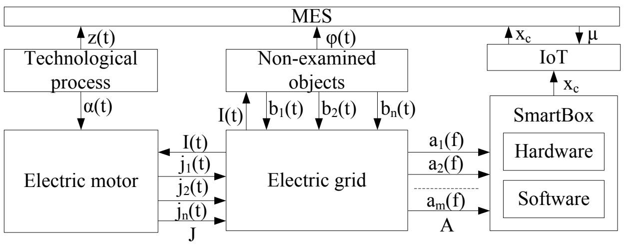

Fig. 2. Integration diagram of a Smart Box device for determining the technical state of the examined object

It should be noted that in most cases the Smart Box consists of two parts: Hardware and Software. The hardware implies the use of microcontrollers, various sensors and switching devices for a data transfer environment. The software implies the software that primarily processes initial information with its subsequent partial analysis. The direct and broader analysis is run at the IoT network level and the general information platform of an enterprise (MES).

The schemes considered (Fig. 1, 2) represent the prototypes of existing decision support systems with one difference, namely the possibility of remote monitoring, planning and management of the examined objects at enterprises and households. This is evidenced by studied and existing developments [6, 15, 16, 20]. Additionally, it should be noted that the application of specialized information platforms, remote databases, specialized software, does not make it possible to unify the process for the creation of SmartBox devices. That results in that the existing software and hardware solutions require special experts in order to analyze technical information by means of costly software and technical tools.

We propose a new concept of the modular cyberphysical system for the early diagnosis of power equipment based on the approaches to using IoT and a group spectral analysis in line with studies [1, 21]. Specifically, a key element of any IoT network is a Smart Box. From the standpoint of an enterprise, there may be several variants of Smart Box devices. In addition to resolving tasks, Smart Boxes can differ cardinally in the architecture of elements of hardware and software, which may lead to additional costs of their integration into the overall IoT network at an enterprise. This may be due to the use of additional software and hardware tools. Therefore, it is proposed to separate each SmartBox device into a separate module that could run, in addition to self-analysis and self-diagnosis, an analysis of compatible Smart Box devices. A model of the modular cyberphysical system using a Smart Box device for the early technical diagnosis of electrical equipment, as well as its information flows, are shown in Fig. 3.

In Fig. 3, the examined IM is connected to a single-phase or three-phase electric grid. According to study [1], IM in the process of their work and due to their own design features form higher harmonics in the electric grid. Therefore, in order to run further analysis of the higher harmonics, the subsystem for current information collection converts an analog signal into a digital one with the subsequent formation of the spectral noise of an electric grid for its analysis [12]. A given subsystem can be represented in the form of a conventional analog-to-digital converter. The task of the database management subsystem (DBMS) is to store and manage all necessary data to enable the correct and efficient operation of a modular SmartBox device. Specifically, such data may include: the data that are responsible for storing a reference sample of the work of the examined IM; the data that are responsible for the current values of parameters in the work of the examined IM. The subsystem for conclusion derivation and display of information is an expert system. It should be noted that the final decision on the technical condition should be taken by MES. This relates to the peculiarities of a technological process and a probability for the error as a result of computation, which in turn may lead to a certain error when drawing a conclusion on the technical condition of the equipment.

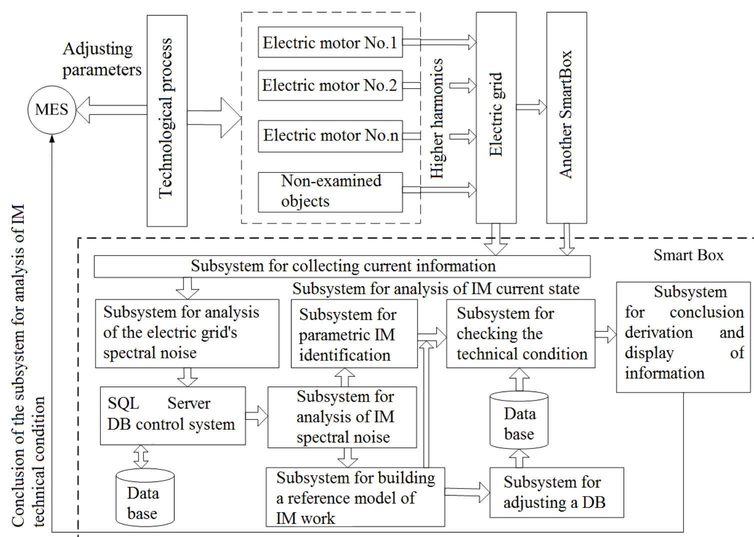

Fig. 3. A model of the modular cyberphysical system using a Smart Box device for the early technical diagnosis of electrical equipment and its information flows

In addition, one should note that the model shown above (Fig. 3) makes it possible to use a single Smart Box device for a group of similar electric motors. To identify each engine as a separate examined object, a spectral analysis is applied [19], which enables its identification among a group of similar devices. It should be noted that the identification of the object is one of the key provisions in the concept of IoT [11, 16].

The proposed approach makes it possible to monitor the current state of equipment using fewer SmartBox devices. Specifically, the total number of SmartBoxes is defined by the type and quantity of equipment used, the pattern of a technological process, and the distance between them. Therefore, a general logical-functional scheme of an enterprise that employs the Smart Box diagnosing devices based on the modular principle can be represented in the following form (Fig. 4).

It should be noted that a single module includes only one Smart Box diagnosing device and a group of similar electric motors connected to the electric grid. Taken together, all of the modules form an information computing cluster. A special feature of the organization of objects into a cluster is the improvement of their performance efficiency and reliability.

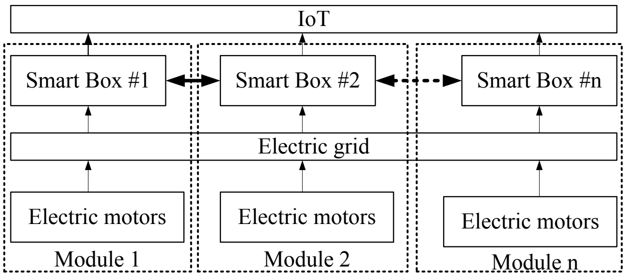

Fig. 4. Modular network of Smart Box diagnosing devices

It is also necessary to take into consideration the fact that a Smart Box cannot arrive at correct conclusions based on experimental (current data) only. This is due to the impossibility of considering all possible situations in a system that may occur. For example, as a result of an error from measurement sensors (ADC), the lack of a precise mathematical model for a pattern in the occurrence of defects, failure of sensors, etc. Therefore, during operation of a Smart Box, there may occur inconsistencies in the classification of situations. To resolve a given problem, one can use fuzzy logic, neural networks, linear discriminant analysis, classification trees, etc.

Based on the considered types of systems [22, 23], we propose, in order to construct a Smart Box expert system, employing a multi-level fuzzy-neural network hybrid system, which would consist of subnets with different architectures (neural network and fuzzy logic). Specifically, the set of all possible situations can be divided in the diagnosing system into a set of standard situations (S1) and a set of emergencies. It is necessary then, based on the results of measuring the current state of electrical equipment, to make the correct decision relating a given situation to one of the sets S1(t) or S2(t). The solution to a given problem is the construction of the rule that recognizes the current situation and computes the membership function (using a fuzzy neural network system).

In general, the functioning of the neuron takes the following form:

$$y=f(s)=f\left(\sum_{i=0}^{n} x_i w_i\right), \qquad (1)$$

where $f(s)$ is the activation function, y is the output of a neuron, w_i are the weights, x_i are the inputs.

A fuzzy neural network system (FNS) should include clear inputs and fuzzy degrees of influences of each input on the situation. FNS would then represent a three-level structure, which would execute control over state of the l-th component (defect) of Smart Box ($l=\overline{1,k}$). The first level is the source data (spectral characteristics acquired in interval $[x_0;x_n]$); the second level performs the filtration of situation attributes $Cj(j=\overline{1,N})$ separating the noise from an useful signal; the third level identifies the situation (there is a defect/no defect).

Weights of the first level are the fuzzy sets x_k (a range of amplitude fluctuation at a corresponding frequency), the set a_k is the result of performing the aggregation,

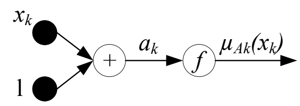

Fig. 5. Construction of a membership function for attribute x_k of defect k

Weights of the first layer are the fuzzy sets A_{ki} $(k=\overline{1,N_l}, j=\overline{1,N_c})$, $\mu_{Ak}(x_k)$ is the activation function, which is derived from the following formula

$$\mu_{Akj}(x_k)=\frac{1}{1+e^{-akj}}. \qquad (2)$$

It should be noted that the second-level weights are assigned in interval [0; 50] and are the mean deviation of amplitude fluctuation at the appropriate frequency.

The structure of NS in general is shown in Fig. 6.

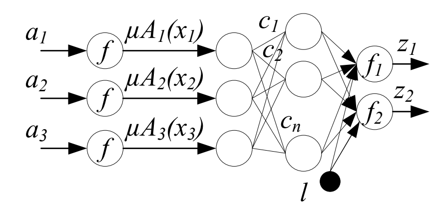

Fig. 6. Structure of a fuzzy neural network system

According to each of the levels of functioning of a fuzzy neural network, it takes the following form:

$$z_m^h = f_m^s\left(\sum_{j=0}^{N_c} w_{jm}^s \cdot \mu_j^s\left(x_1,..,x_N\right)\right), \qquad (3)$$

where s=2, 3 are the numbers of the corresponding level, h==1, 2 is the number of the resulting state, f_m^s is the activation function of the output layer. Membership functions shall be determined by the methods of an expert estimation [24–26].

Therefore, the proposed fuzzy neural network system that would act as an apparatus of logical derivation for Smart Box could enable solving the tasks on monitoring the current state and on the early diagnosis of electrical equipment in real time.

5. Results of modeling the operation of a modular cyberphysical system for the early diagnosis of energy equipment

The feasibility and rationality of the proposed concept for a modular cyberphysical system for the early diagnosis of IM was analyzed using the simulation and computer analysis by the Monte Carlo method. This method is statistical, that is, it simulates rather well the real distribution of sample statistics under condition of a large number of experiments [24]. The applied generator of random numbers was a random number generator, which is part of Framework 4.5 based on the millisecond timer of a computer [27].

It should be noted that, according to available studies [1], it is necessary, when monitoring the current state of IM, to employ 6 or more characteristic frequencies (CF) for the identification of electric motors. However, as CF is a training sample for a neural network, the quantity of these frequencies then could affect the learning time, which could influence the overall reaction time of an information system.

An analysis of influence of the number of CF on the learning time was performed by computer simulation in the mathematical software Matlab Fuzzy Logic employing the program m-function ANFIS, in which we applied CF as input variables. The algorithm to train the ANFIS network to define parameters for the membership function was the error backpropagation method based on the method of gradient descent. The results are shown in Fig. 7.

Thus, the result of computer simulation shows that the shortest learning time could be achieved when using 1 to 6 characteristic frequencies.

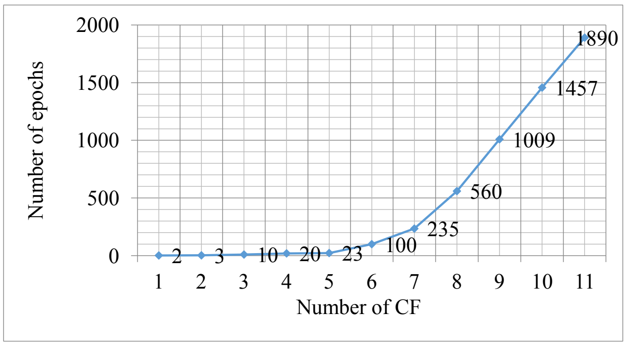

Fig. 7. Results of modeling the influence of the number of characteristic frequencies on learning time

We examined, for each type of a modular Smart Box device, the time of the system's reaction to object τ. The time of reaction is to be understood as the time over which a Smart Box derives a conclusion on the technical condition of electric motors. At each stage of the experiment, the number of examined motors varied from 1 to 5. Spectral characteristic and a possible defect for each motor were generated randomly. 5 CF were chosen as the input sample for a neural network.

Results of comparing the reaction of a standard and a modular Smart Box device are shown in Fig. 8.

The modular structure of a Smart Box was analyzed by increasing the number of diagnosed electric motors from 1 to 5 and by increasing the number of nodes in a cluster from 1 to 4. A node of the cluster was a Smart Box device module.

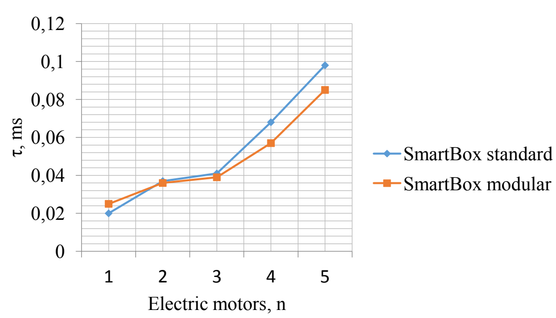

Fig. 8. Results of testing the standard and modular Smart Box device

The type of a cluster was the model of a cluster system of type HPC (cluster for high-performance computing). Results of tests are shown in Fig. 9.

Thus, based on the results of testing, we can conclude that the reaction time in the cluster system is longer than that in a standard one, by about 30–35 % under condition of using 3 or 4 nodes in the cluster.

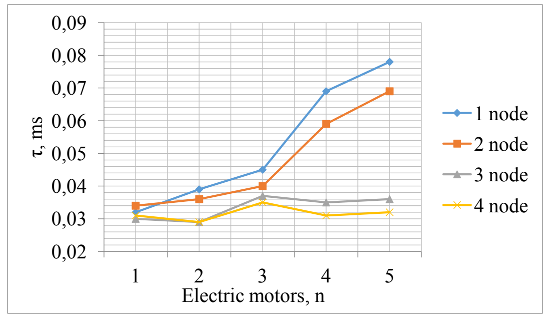

Fig. 9. Results of testing a cluster system composed of the Smart Box nodes

It is obvious that at an actual enterprise the obtained indicators may differ according to different types of situations. However, the electric motor defect recognition quality would be higher in the case of applying a modular Smart Box system.

According to the calculations performed, the standard deviation was Sa=2.78 Hz, an absolute error for a 95 % reliability (Student's coefficient $t\alpha$=1.984 at α=0.05 and n=100) amounted to Δx=5.79, a relative error was ea=3.47 %. We also tested the reproducibility of experiments (homogeneity of variances) Gp=0.3294 at the boundary tabular value Gk=0.372.

6. Discussion of results of studying the proposed structure for a modular cyberphysical system

A solution to the task on the technical diagnosis of electrical equipment at an enterprise was found by employing the concept of cyberphysical systems. That is, a combination of Smart Box devices with intelligent manufacturing (MES), at which each Smart Box is capable of self-diagnosing both separately and in combination. Specifically, the use of modular Smart Box devices makes it possible to reduce the number of equipment items employed for diagnosis. Additionally, there is a possibility to build clusters of Smart Box modules, which makes it possible to improve the reliability and performance efficiency of IoT system in general.

The proposed structure for a modular cyberphysical system for the early diagnosis of power equipment in the absence of integration into the overall information system of an enterprise could represent part of IoT in a private household. It could also form an element of the system "Smart Home" and work independently. For example, for diagnosing household appliances, such as hair dryers, washing machines, fans, etc.

The advantage of the proposed system is the flexibility in its setting as it makes it possible to use, as a subsystem for conclusion derivation and display of information, a fuzzy derivation system. The structure of a fuzzy system makes it possible to easily change parameters for term sets, which in turn could improve the quality of defects recognition according to special features or conditions of use.

In addition, the benefit of the system is the capability to create a cluster of modular Smart Box devices that provides for an opportunity to work in tandem with other modules.

That makes it possible to exchange information with neighboring Smart Box devices.

The disadvantages of a given intelligent system include the inability to work with power units that do not include IM. In addition, the disadvantages include a probability of errors related to the quality of electric grid. Specifically, surges in voltage, the occurrence of higher harmonics due to the energy equipment that is several times more powerful.

A prospect for the further development is solving a task on the creation of the concept of alternative global IoT for technological devices. In turn, that would make it possible to significantly improve the quality of communication between devices, thereby increasing an informative basis for diagnosis.

7. Conclusions

1. We have proposed a modular structure of the cyber-physical system for the early diagnosis of power equipment based on the principles of IoT. Specifically, modular Smart Box devices that are capable, based on a spectrum-current analysis, of identifying electrical equipment and further diagnosis. Employing a given approach makes it possible to unite all IoT devices in clusters, thereby improving performance efficiency and reducing the reaction time of the system.

2. According to the structure of the subsystem for conclusion derivation and display of information, we chose, as informative attributes, the characteristic frequencies that identify an electric motor in the power grid. We have proposed using the structure of a neural-fuzzy network, which consists of 3 layers. A special feature of this system is the possibility to change the number of terms for input variables in order to improve the quality of IM identification. Specifically, for systems with small generation capacity, in order to increase the diagnosed IM within the cluster, it is advisable to reduce the set to, for example, 3–4 CF.

3. We established in the course of training a neural-fuzzy network that in order to achieve a smaller value for a standard error in training and to improve the quality of IM identification in the power grid, it is necessary to apply a training sample with large values of characteristic frequencies. It should be noted that an increase in the number of CF contributes to an increase in the number of training epochs. However, an increase in the number of training epochs increases the total time of a neural-fuzzy network learning. This, in turn, affects the overall reaction of the system. It was established empirically that the optimum number of neurons in the outer layer (N) is 5–6 that corresponds to the number of CF. In this case, the standard error is within E=10^{-3}. Due to this, we obtained the best result of prediction with a relative deviation within 3 %.

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