Complex Method for Determining the Technical Condition of Electronic Devices Based on a Cognitive Model, Petri Nets and Artificial Neural Network

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***Abstract*—The paper proposes a complex method for determining the technical condition of electronic devices (TC of ED) based on building a heterogeneous cognitive model (HCM), a simulation network model and formation of an artificial neural network (ANN). The well-proven and established in modeling discrete processes Petri net acts here as a simulation network model. The novelty of the given method is the combination of the HCM and the Petri net to obtain additional information about TC of ED and to build on their basis the ANN for making diagnostic decisions under measuring and expert information. ANN is used to solve the classification problem that allows one to identify the state of the ED which are characterized by certain parameter values and range it to one of the several pairwise non-intersecting specified classes. The paper presents a table of flowchart conversion into HCM, Petri net, as well as algorithms for converting HCM and Petri net into ANN with some assumptions. This allows one to avoid the select problem of the ANN structure, which is carried out on the basis of the operational personnel experience and scores of attempts to conduct training. The method proposed is illustrated by the example of determining the TC of microcontrollers in control systems.**

Keywords— heterogeneous cognitive model, Petri net, neural network, technical condition of electronic devices

I. Introduction

The process of diagnosing ED for various purposes is a rather complex process and is an important technical task. First, solving the problem requires prompt receipt and processing of large amounts of various information, as well as an expert analysis of this information. Second, the problem is complicated by the limited time allotted for troubleshooting and determining the TC of ED, which in most cases are quite remote from service centers. Third, the task is complicated by the need to obtain diagnostic estimates when recognizing the type of the TC of ED directly when the device is in operation, i.e. in real time. Therefore, the ED diagnostics is currently a very urgent task.

Currently, a sufficient number of methods for ED test diagnostics have been developed. However, they have significant drawbacks. Firstly, the ED removing from service is required which does not allow using these methods directly during the ED operation. Secondly, special equipment is needed to generate test signals that are sent to the controlled object when it is disconnected from the operating mode [1-5]. This is the reason to develop such decision support methods for the ED diagnostics that would ensure, on the one hand, the maximum completeness of the obtained assessment of TC of ED, and on the other hand, the conduct of a diagnostic experiment directly during the ED operation.

In this regard, this paper proposes a complex method for determining the TC of ED based on the building a heterogeneous cognitive model, a simulation network model and the formation of the ANN structure on their basis.

II. Algorithm flowchart interpretation in HCM and Petri net

The algorithms that implement the decision support methods in the ED diagnostics are normally represented in the form of flowcharts. However, the flowchart may have many errors and drawbacks (for example, it does not reflect the interaction between the parameters that impacts the TC of ED, as well as the operational personnel of the process). This leads to conflicts in the control system and to the lack of further opportunities for the use of mathematical apparatus or the modeling the process of determining the TC of ED represented by flowcharts.

In this regard, it is proposed to interpret the flowcharts in HCM and Petri net. As HCM make it possible to reflect process problems in a simplified form (model); to explore through scenarios of emergency situations; to find ways to solve them in model situations, and to investigate the structure optimality. Petri nets allow one to study not only the operability of simulated systems that change over time, but also to determine the previous system states, including never reached ones (to model processes), and also to visually represent the dynamics of changes in TC of ED depending on the parameters [6, 7]. Flowchart algorithm interpretation in HCM and Petri net is shown in Table 1.

Table 1 shows that the flowchart is very similar to the Petri net. The nodes of the flowchart are replaced with Petri net transitions, and the arcs are replaced with positions (vertices – with a place in the Petri net) [8, 9].

It should be noted that the constructed HCM used in the ED diagnostics should have the following properties:

- No reciprocal links.

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- HCM should preferably include cycles that are involved in the analysis of structural stability and perturbation stability by initial value [10].

TABLE I. FLOWCHART ALGORITHM INTERPRETATION IN HCM AND PETRI NET

Structure name	**Flowchart element**	**Heterogeneous cognitive model**	**Petri net**
Sequence (start/stop)	Activity		
Branch	Condition Activity 1 Activity 2	–	
Parallel processing	Activity 1 Activity 2 ... Activity n	...	...
Parallel composition	Activity 1 ... Activity n Activity	...	...

Constructed Petri nets should have the following properties [6]:

- Limitation occurs if the number of tags in any position of the network cannot exceed the K value. If the number of tags increases unlimitedly, then there is a danger of unlimited growth of queue lengths.
- Security is a special case of the limitation, K=1. The Petri net is safe if it can't have more than one tag in each of the positions under no circumstances.
- Reachability is the ability of the network to move from one given state (characterized by the distribution of chips) to another one. Here, the dead-end markup reachability may also occur – this is the finiteness of the structure functioning. Thus, when modeling the process of determining the TC of ED, such a property must be absent since it prolongs the operation of this process without errors and freezes. The problem of dealing with deadlocks is becoming more and more urgent and complicated at the present time. When modeling the process of determining the TC of ED, the operational personnel try to analyze possible emergency situations using special models and methods [10, 11].
- Liveness is the ability of triggering any transition in this network at the initial markup (functioning of the simulated object). The lack of liveness means either the redundancy of the parameters that characterize the TC of ED when diagnosing it, or indicates that loops, deadlocks, and locks may occur.

III. BUILDING THE ANN BASED ON THE HCM AND PETRI NET

After modeling the process of determining the TC of ED based on the Petri net, it is proposed to solve the classification problem, which allows one to recognize the TC of ED and range it to one of several pairwise non-intersecting specified classes. It should be noted that the classification task is much more complicated with a large number of controlled parameters; a decision about the TC of ED is made on the basis of these parameters values. ANNs are proposed to be used for solving the classification problem as they provide high recognition efficiency.

To avoid the problem of selecting the ANN structure which is carried out on the basis of the experience of the operational personnel and many attempts to conduct training, it is proposed to perform certain transformations.

Fig. 1 shows the transformation of HCM to ANN.

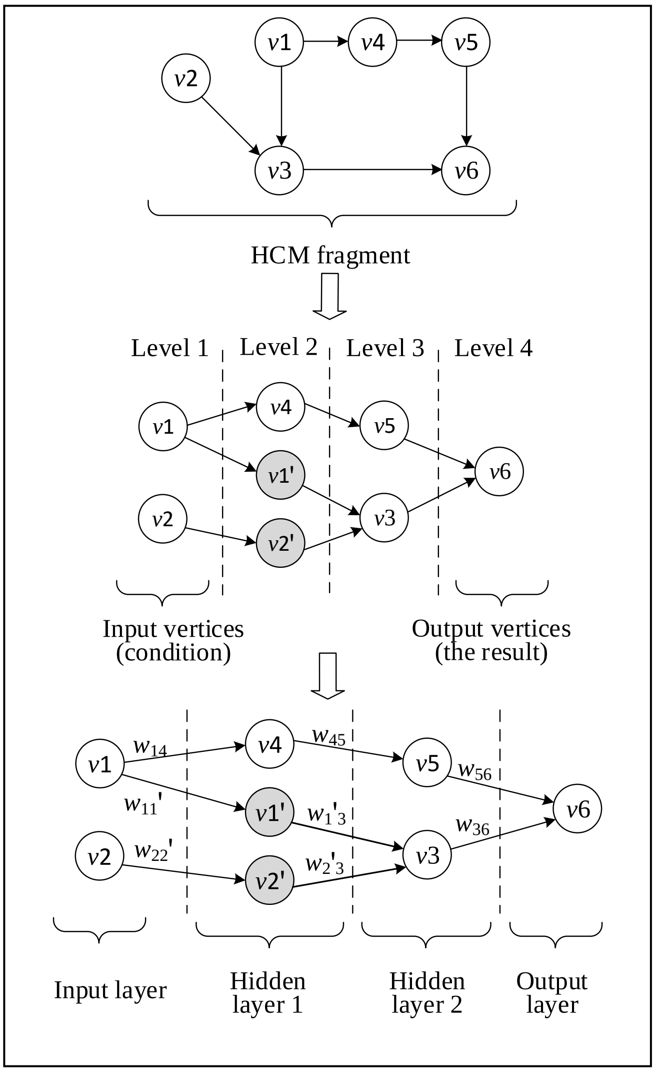

Fig. 1. Transformation of HCM to ANN.

To build an ANN, it is necessary to reduce the HCM to the ANN structure. To do this, the HCM vertices are distributed in a hierarchy (levels) in accordance with the conditions [12]:

- The following vertex must not be higher than the previous vertex.

- Vertices of the same level must not be connected to each other.
- All arcs must follow the same direction.
- The arc must not be longer than one level, otherwise dummy-based vertices are added.

Here, the vertices v_1' and v_2' are dummy-based and highlighted in gray.

To build ANN based on a Petri net, some authors in [13-15] propose to perform transformations using the following assumptions:

- Events and transitions in the Petri net are converted into neurons.
- Arcs between events and transitions in the Petri net are transformed into connections in a neural network.
- Protective conditions at transitions during transformation are not transferred to the neural network.

Fig. 2 shows the transformation of the Petri net to ADD.

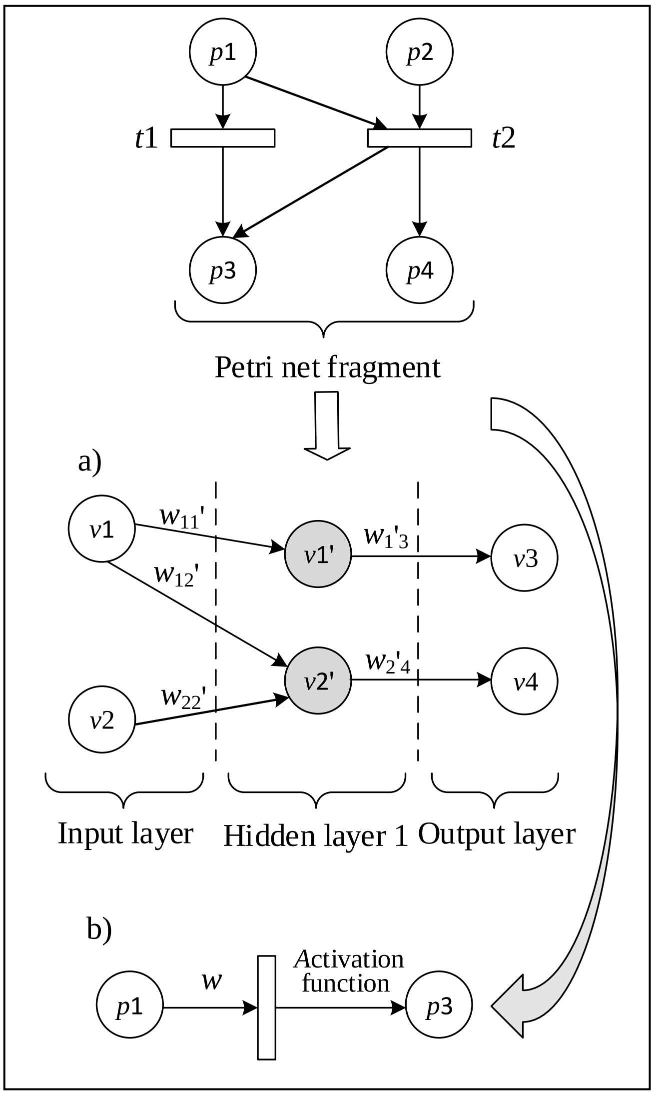

Fig. 2. Transformation of the Petri net to ANN.

In Fig. 2 a), transitions t_1 and t_2 are transformed into neurons (vertices v_1' and v_2'), w – weight representing the impact of input places on transitions.

The considered transitions are necessary for obtaining the initial structure of the ADD and its further training.

IV. Example of Microcontroller TC in Control Systems

To diagnose the microcontroller TC, the HCM for the impact of power quality indicators (PQI) on microcontrollers has been developed. Fig. 3 presents HCM fragment.

Here, v_1 – frequency deviation; v_2 – voltage fall duration; v_3 – negative-phase-sequence voltage unbalance factor; v_4 – zero-phase-sequence voltage unbalance factor; v_5 – voltage unbalance; v_6 – flicker value; v_7 – n - voltage harmonicity ratio; v_8 – temporary overvoltage ratio; v_9 – C- phase voltage; v_{10} – A-phase voltage; v_{11} – B-phase voltage; v_{12} – lightning impulse voltage; v_{13} – voltage deviation in A-, B-, C- phases; v_{14} – voltage variation range; v_{15} – voltage THD; v_{16} – voltage fluctuations; x_{17} – voltage nonsinusoidality; and diagnostic factors*:* v_{18} –climatic conditions; v_{19} – TC of AM serviceability.

To determine links between parameters (vertices), a scale was established to assess the nature and strength of links [16]. The structure analysis of the HCM built allows the operational personnel to find out the best parameter values that characterize the microcontroller TC, to determine the impact degree between parameters, and to identify the most significant parameters from the parameter set.

To simulate the process of determining the microcontroller TC in control systems, the simulation network model built is used, which provides not only tracking the current state of microcontrollers and carry out various variations of diagnostic measures by simulation, but also planning the diagnostic measures. A fragment of the simulation network model for determining the microcontroller TC is shown in Fig. 4.

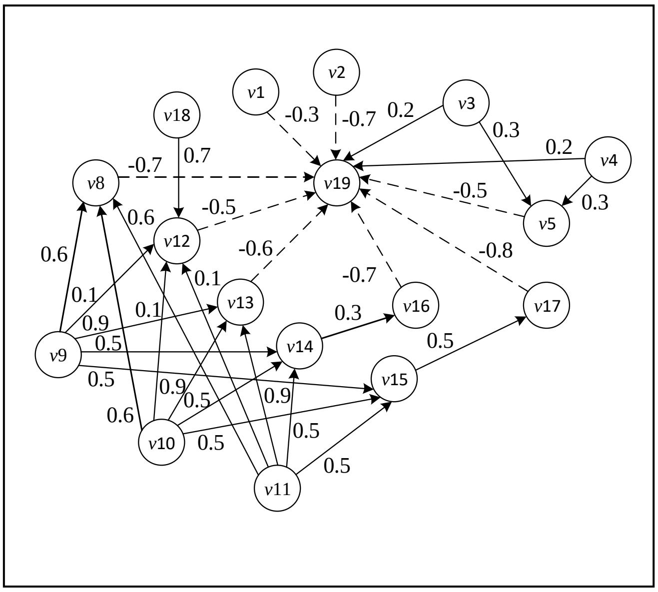

Fig. 3. Heterogeneous cognitive model for the PQI impact on TC of ED.

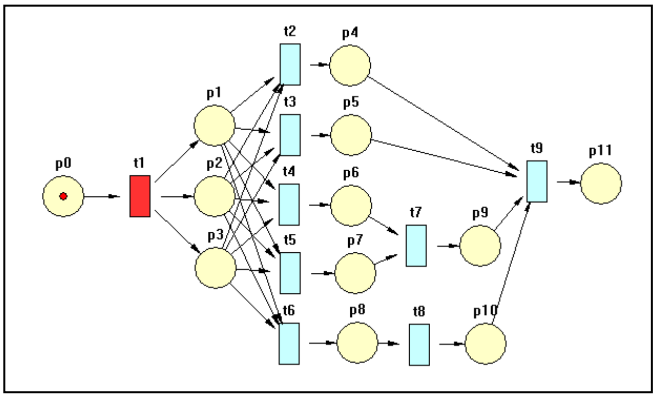

Fig. 4. Fragment of the simulation network model for determining the TC of microcontrollers.

The simulation network model for determining the TC of microcontrollers includes:

- Positions – intermediate states of parameter development, factors $P = \{p_0, p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8, p_9, p_{10}, p_{11}\}$.
- Transitions – interaction of states $T = \{t_1, t_2, t_3, t_4, t_5, t_6, t_7, t_8, t_9\}$.
- Label parameters – time-varying parameters of microcontrollers.

The Petri net shown in Fig. 4 has the boundedness property, since it follows from the minimum generating set of S-invariants that all positions in it correspond to positive invariants (non-zero coordinates). This means that no position in the network can accumulate an infinite number of chips. In addition, all positions in the network are reachable, i.e. the model does not contain any extra positions.

The ANN built on the basis of the HCM for determining the microcontroller TC contains 3 neurons in the input layer, 11 and 5 neurons in both hidden layers, and 1 neuron in the output layer. A sigmoidal activation function was used for all layers. ADD training was performed using a database that contained 1900 observations of all parameters.

The training included 1400 observations, and the remaining 500 observations were not included in training (test sample). To evaluate the ADD performance, the accuracy was calculated: $P =$ 0.9836.

ANN built on the basis of the Petri net contains 4 hidden layers. With the same amount of training and test data described above, the training accuracy was $P = 0.9741$.

V. Conclusion

The paper proposes a complex method for determining the technical condition of electronic devices based on the building of a simulation network model (Petri net), a heterogeneous cognitive model and the formation of an artificial neural network on their basis in the conditions of measuring and expert information.

The use of HCM makes it possible to determine the impact degree between parameters, to identify the most significant parameters from a variety of parameters, as well as to make scientifically based management decisions regarding the ED serviceability. The use of a Petri net-based model in modeling the process of determining the TC of ED allows one to determine which states of the system are reachable, to clearly coordinate the interaction of ED parameters, and also highlight the most important parameters depending on the TC of ED.

The results obtained showed that HCM-based ADD has a high accuracy of P =0.9836, which means that the model allows one to effectively diagnose the ED, as well as predict the TC, taking into account the multifactorial nature and knowledge of the operational personnel.

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