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Intelligent system for monitoring and controlling the technical condition of mechatronic process facilities

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Introduction. Digital systems that control the maintenance of separate mechatronic process facilities (MPF) and sets of production machines are mainly considered. Numerous issues on maintaining the reliability of the condition and emerging malfunctions, as well as the multifactorial nature of the using the existing monitoring and diagnostic systems, are noted. In this regard, the relevance of the tasks of developing methods of processing equipment maintenance to make decisions under the data veracity and limitation is specified.

Materials and Methods. To analyze the criticality of the technical condition, an assessment of the efficiency of the autonomous control of the device state is formed. The method of the neuro-fuzzy system is used to determine the aggregate criterion of criticality. It is proposed to apply this approach to develop recommendations on equipping a production facility with the necessary means of maintaining overall performance and reliability.

Results. The solution provides predicting the development of the state of mechatronic process equipment, alerting personnel in case of emergency and other dangerous conditions, and, if necessary, updating or adjusting control programs. Provision is made for performing of some of the technical state maintenance functions by the mechatronic facility itself, i.e., equipment self-service. The concept of "autonomous management of the technical condition" is formulated. The system structure and control functions are considered. It is noted that the implementation of the systems under consideration will significantly increase the efficiency of the equipment use. The performance of the autonomous control of the device or MPF in general is evaluated in accordance with ISO 13381-1: 2004. Based on this standard and the data presented earlier, a neural network structure is built to assess the autonomy of state management. The system training efficiency is considered taking into account the standard deviation of the network outputs from the target values of the training sample.

Discussion and Conclusion. A list of the basic control functions at different levels of maintenance autonomy is presented: from alarm for failure prediction to complete maintenance autonomy without the direct involvement of an operator.

Keywords: digital systems, autonomous maintenance, technical condition management, critical condition.

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Introduction. For more than 50 years, serious developments have been carried out in the field of machine maintenance, which focus on methods and standards for maintaining an operational condition of the equipment. New devices and techniques are being developed for determining emergency conditions, identifying faults, and predicting a remaining life. The condition control and monitoring are essential for production mechatronic facilities of the industrial enterprises, such as machines with computer numerical control (CNC), forging and foundry machines, automated flexible transfer lines, etc. Equipment maintenance methods take various forms [1, 2], each of which has pros and cons that affect the level of control of the production condition of the equipment. Such control and providing the reliability of machines are urgent scientific tasks. Numerous studies are devoted to this topic. An example is the works [3–14]. Russian and foreign scientists mainly consider the creation of automated monitoring and diagnostic systems. When using artificial intelligence methods for automation, processor modules are developed; they have acquired a general name of "e-maintenance systems".

Digital systems of electronic service are implemented by a collection of hardware-software components, which are designed to receive sensory information and assess the equipment status realtime. They provide predicting state changes in the production equipment and its components, generating messages on the need for certain actions on the part of experts, and, in some cases, changing the equipment operation parameters. The systems under consideration are used for personal diagnostics and monitoring of the technical condition of separate mechatronic objects. In addition, they are involved in the service system of a group of production machines.

The focus of current research is the creation of programs and algorithms for service, and analysis of its results. Developments in the field of service quality and efficiency of the equipment utilization are aimed at this. In modern production sectors, such systems as Casip, Enigma, Icasame, RemoteDataSentinel, Intermor, INID, IPDSS, Proteus, MRPOS, WSDF, Telma, etc., are used for servicing [15–18].

It stands to mention multiplicity of issues on maintaining the reliability of the condition and arising faults, as well as the multifactority of the application of existing monitoring and diagnostic systems. In this regard, the tasks on the development of methods and techniques for the processing equipment maintenance, which provide decision-making under the conditions of data veracity and limitation, remain relevant.

In recent years, the basic functionality of control, monitoring and diagnostics systems, tools, methods and technologies for servicing, forecasting and analyzing equipment status has changed. They are reoriented from the analysis of the technical condition to the prevention and detection of malfunctions at the early operational stages. Such control methods are being developed that allow minimizing the impact of emerging malfunctions on the performance and downtime of the equipment, on the number of failed parts and the frequency of failures. Ultimately, new approaches reduce economic losses.

The urgent issue is the development of a new solution based on the intelligence of the system. It is about creating an automated autonomous service management and, as a consequence, about control over the autonomous technical condition of the equipment.

Autonomous maintenance (AM) [19] is a comprehensive definition. In relation to machines, it implies such an automatic performance of service and maintenance functions, in which the equipment independently maintains its operability (self-service). If human intervention in the maintenance is wanted, the service functions remain hand-driven by an operator, that is, the problems are fixed promptly, without involving external repair services and until the end of the production run.

The self-servicing of mechatronic process facilities (MPF) in the sense presented earlier is not yet an implemented solution, but a promising one. It is expected that the methods of artificial intelligence in the field of diagnostics and servicing will receive a level of knowledge equal to the level of staff.

Materials and Methods. At the present stage of technology development, we consider the concept of MPF AM in the following interpretation. The purpose of the solution is maintainability based on an assessment of the state of the component and the MPF in general. For this, an independent automated control purposefully displays the status and required impacts on the MPF components [20].

As noted earlier, the basic approach to creating and developing autonomy in managing the operability of the processing equipment is the application of artificial intelligence and intelligent control methods under the conditions of uncertainty and fuzziness of the knowledge provided [21].

Research Results. Under the conditions of uncertainty, we consider the control procedure as the dependence of the real state on the goal state (successful performance):

$$R^* = A \to B,$$

where A and B are expert reports on the real and goal state of MPF.

Presentation of the result of fuzzy inference Y depends on:

— observed data X obtained by the diagnostic system;

— knowledge system $A \to B$;

— coefficient K, which is responsible for a possible measurement error.

Therefore, the derivation of Y takes the form:

$$Y = X \times R^{*}+K = X \times (A \to B) + K,$$

where $Y = \{Y_1, Y_2, ..., Y_m\}$ are parameters responsible for the equipment state management and for log output for the operator; $X = \{X_1, X_2, \ldots, X_n\}$ are data on the input state of the equipment.

Using this interpretation of the maintenance autonomy, we consider the structure and functions of the MPF AM (Fig. 1).

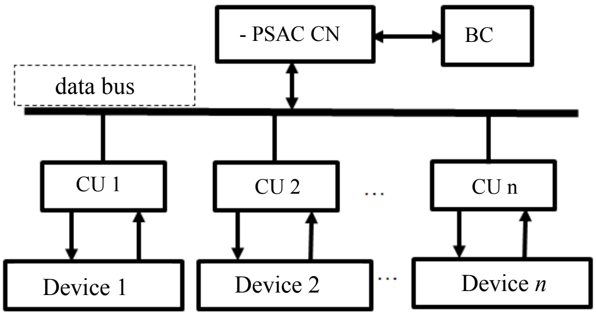


Fig. 1. Structure of the control system of the equipment technical condition

Here, signals from the diagnostic system sensors arrive at the control device not directly, but through the control unit of the technical state (TSCU) of the nodes.

Nodes of the control unit receive data from the central node of the autonomous control of the process system (PSAC CN), which:

— coordinates the operation and maintenance of all machine components;

— processes data received from diagnostic systems;

— on the basis of these data, analyzes the state, predicts the development of malfunctions and makes decisions on the required actions on smooth operation of the equipment.

In the proposed approach to the generalized functions for the MPF technical condition management, control methods using signaling about the risk of failures, emergency situations, the need for a fuzzy device working band, etc. [22], are considered.

An electronic service system (for example, e-Mind Machine) can provide information communication between the PSAC of an object through IS with equipment maintenance and repair units and enterprise management structures [23].

The autonomous control functions include decision-making on the system behavior in the event of a malfunction; consequently, the system should be trained during operation. Thus, diagnostic and monitoring methods are being improved, which provides eliminating previously unknown malfunctions.

The analytical methods are complicated (or impossible) in adequate presentation of the state and changes of MPF. This is due to the following maintenance features of this equipment:

— structural complexity of the mechatronic object consisting of a large number of nodes;

— variety of factors affecting the reliability and performance, accuracy and productivity of machines;

— wide range of properties of the materials from which the parts are made;

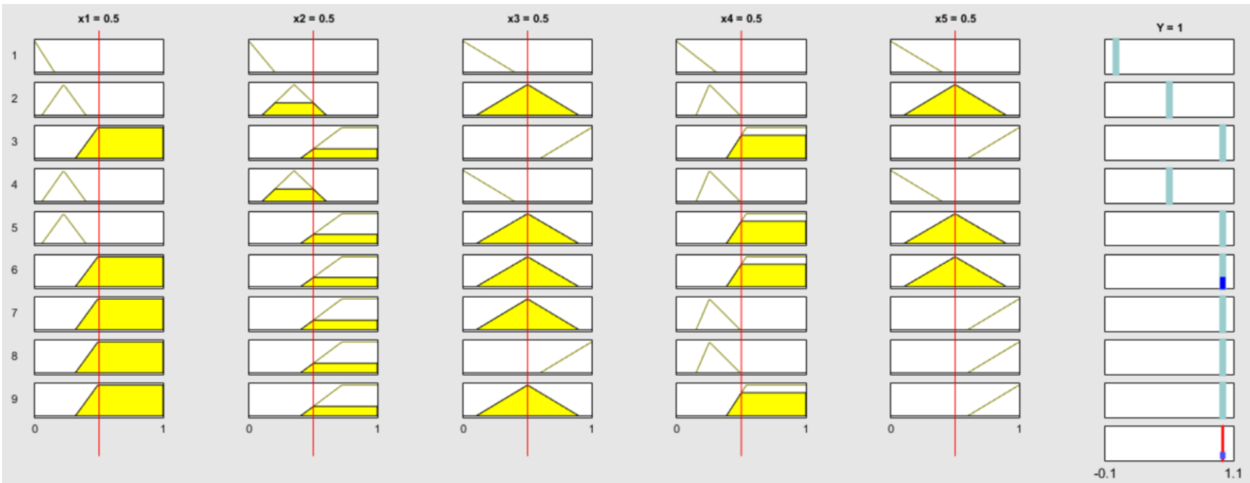
— variety of requirements for functionality, parametric characteristics and performance of units, modules and devices in accordance with their purpose, accuracy characteristics, implemented production tasks.

The e-MindMachine concept provides management based on data on the real state of the facility and operational history. In this case, the development of faults for each unit is predicted. The application of the gamma-percentile life of reliable operation is proposed if statistical data are available or a border health band is used [22–24].

When developing PSAC of process facilities, it is possible to provide a ranking of autonomy levels depending on the maintenance unit used at the enterprise [25, 26]. It also depends on the criticality of the machine in the overall production. In this case, criticality determines significance of one or another of its units for the enterprise. The higher the criticality, the more economic, physical or temporary losses an enterprise suffers from the downtime of this unit. Such data is based on the equipment usage statistics, the number of failures, downtime, the cost of spare parts and manufactured parts, the number of work shifts, etc.

When analyzing the criticality, it is also important to consider the future conditions of the machine, the degree of development of malfunctions, and the planning of the acquisition of spare parts. This is necessary to assess the residual life and to calculate the time before a possible failure under the conditions of uncertainty and stochasticity of data on the equipment status. Criticality assessment helps to find out the significance of the given equipment unit for the enterprise, and how much stop service and work resumption cost.

To analyze maximum number of parameters that affect criticality of failures, we construct a system for the generalized assessment of the MPF technical condition criticality. For the output aggregate criterion of criticality, we use an ANFIS-based neuro-fuzzy assessment in MATLAB. As an example, we consider the failure criticality of the spindle assembly of a HAAS SMM vertical milling machine (Fig. 2).



a) *b*) *c*) *d*) *e*) *f*)

Fig. 2. Failure criticality assessment. Red vertical line is indicator 0.5:
(a) equipment performance and accuracy; (b) costs of equipment repair and spare parts; (c) equipment downtime; (d)
(b) number of equipment (unit) failures for a certain period; (e) time for fault identification and repair;
(c) (f) $Y = 1$ is full compliance to output parameters

Fig. 2 shows that the input actions in the neuron-fuzzy system are responsible for all the key aspects which concern the equipment operation at the enterprise [27]. As a result, when logging-out, we obtain a generalized criterion of criticality Y whose value can vary from 0 to 1. Here, $Y = 0$, the input parameters do not meet the production requirements. According to the monitoring data, the parameters went beyond $0 < Y < 1$, but an expert can make a conclusion on the availability of equipment (for example, at $Y = 0.75$). Using this criticality assessment technique, when determining the operability of the same type of equipment, it is possible to indicate a response range for emerging malfunctions and create a new decision-making system under uncertainty. Thus, the most significant (critical) equipment receives maximum response from the operator and maintenance personnel for its operability.

Fuzzy logic methods simplify the intelligent control system and evaluate immediately the state of an object. This is an autonomous management of the technical condition of the facility, so you need to understand how deep autonomy can be. A machine is considered together with an operator, which means that the equipment is automatically controlled by the actions of the operator as well. Management levels depend on the functions assigned to human.

Level 1. Control. It is determined by the presence or absence of an emergency malfunction, which causes equipment shutdown.

Level 2. Diagnostics. The data analysis on the equipment condition is carried out by the built-in or mounted sensors.

Level 3. Monitoring. The current level of performance is determined, operational or tactical decisions are made.

Level 4. The operator performs all basic functions without machine automation. They can be displayed as instructions.

Level 5. The operator performs part of the functions that do not require deviation from the production tasks.

Level 6. Autonomy of the MPF service without the intervention of an operator.

If it is necessary to maintain the equipment operability at a high level, it is advisable to use monitoring (level 3). The use of some automation at the 4th level seems to be a transition to the creation of intelligent service systems.

The implementation of the systems under consideration increases significantly the equipment efficiency. The productivity of the autonomous control of a device or MPF is generally evaluated in accordance with ISO 13381-1: 2004. Based on this standard and the data presented earlier, we construct the structure of a neural network for assessing the autonomy of state control (Fig. 3).

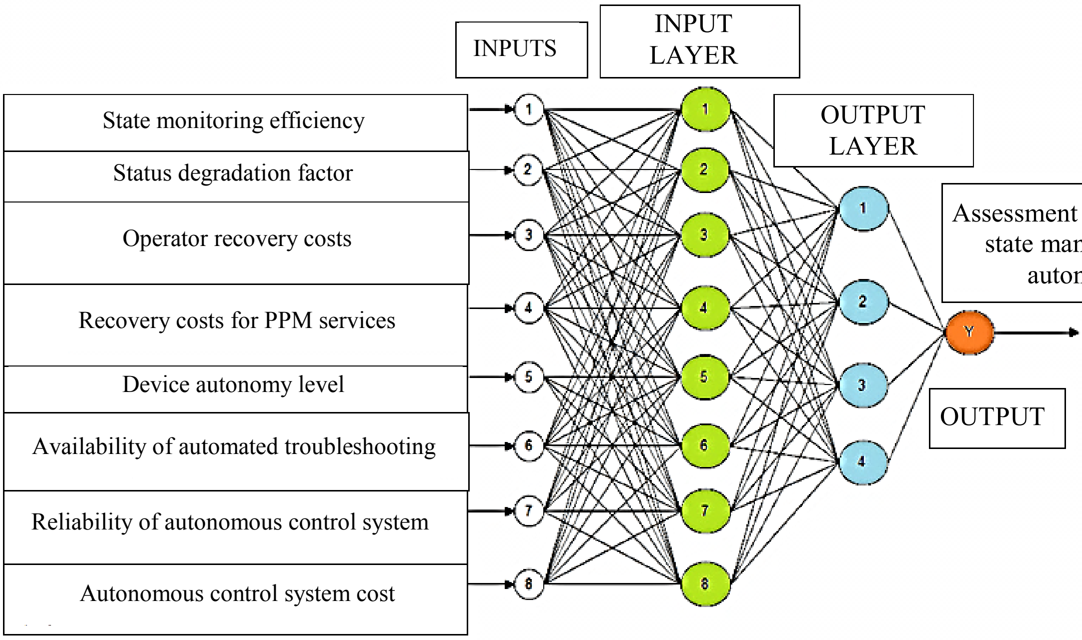


Fig. 3. Structure of neural network assessment of the state management autonomy[1]

Learning efficiency was evaluated with account of the standard error of the deviations of the network outputs from the target values of the training sample [20].

Discussion and Conclusion. The paper presents the basic principles and approaches that provide designing, creating and improving autonomous systems for management of the technical condition of the process facilities. The operation of such systems implies significant uncertainty and limited aprior and current data for decision-making. This necessitates the introduction of state-of-the-art technologies and methods of artificial intelligence.

The authors' view on the role, functions and construction of maintenance systems for MPF and other equipment is presented. The proposed approach is based on the application of digital information processing and decision-making technologies, which is due to the growing complexity of MPF automation. In each process system, the principles of openness, autonomy, and control of fine movements are implemented to one degree or another. This should be considered when designing workpart procedures and when implementing processes to maintain the equipment operability.

[1] PPM — preventive and predictive maintenance.

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Claimed contributorship

A.K. Tugengol'd: concept development; research objectives and tasks setting; mathematical rationale of problems; theoretical description of solutions; development of state management levels; assessment of the state management autonomy using a neural network. E.A. Luk'ynov: mathematical calculations; building block diagrams; rationale for using different management levels; conclusion formulation. R.N. Voloshin: writing a review on the topic; text processing; assessment of criticality; work with standards; building the neural network structure. F.V. Bonilla: work with foreign sources; text processing; building dependences based on the neural fuzzy ANFIS system in MATLAB.

All authors have read and approved the final manuscript.