Adaptive Control System for Technological Process within OSTIS Ecosystem

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***Abstract*—In this paper an approach to building a hybrid intellectual computer system for adaptive control of a technological production cycle is being proposed in the form of an ostis-system solver based on the ontology of the "technological production processes with probabilistic attributes" domain knowledge. The idea of development and implementation of mathematical models of neural network regulators for control optimization problems is the basis for the system solver. Such an implementation makes it possible to integrate the proposed solution with other developed solutions as well as the company's software in order to allow building intellectual systems for automated control, recommendation systems and decision support systems, information support systems for the company's personnel.**

***Keywords*—technological production process, adaptive control, neural network, reinforcement learning, Industry 4.0, standard**

I. INTRODUCTION

The constant efforts of scientific and technological advances in the sphere of optimization of production systems operation require the development of up-to-date approaches to adaptive control of production processes that would include elements of artificial intelligence, neural network modeling and development of intellectual computer systems of new generation.

In this paper an approach is being proposed for building a hybrid intellectual computer system for adaptive control of a technological production cycle within the framework of OSTIS Ecosystem. The formal description of the control object is based on ontologies of the "technological production processes with probabilistic attributes" domain knowledge and ISA 5.1, ISA-88, ISA-95 standards, implemented through the means of OSTIS Technology.

Control adaptation is implemented using the means of software-hardware coupling of neural network regulators and hardware control system of the technological object in real-time.

The idea of the hybrid intellectual system for adaptive control is based upon development and implementation of mathematical models of neural network regulators for solving problems of control optimization, implementation of methods and algorithms of synthesis of feedback control for technological cycle, depending on changing parameters of the control object operation.

II. TERMS AND DEFINITIONS

The central concepts within the knowledge domain under consideration are technological process (technological cycle) and probabilistic technological process [2].

1) A technological process (TP) (technological cycle) of production is a sequence of interconnected operations, that is defined by technological documentation, directed at the object of process with purpose of producing the required output. Within ISA-88 standard's procedural control module TP is defined as a procedure, that produces a batch of product (that may be a final product or intermediate product used in the further stages of production of the final product).
2) A technological operation is part of a technological process, that is being run continuously at one workplace on one or more simultaneously processed or assembled products by one or more operators. Within ISA-88 standard it is defined as operation that results in substantially altered product properties. Operations can be run by an operator who can start, pause and resume them. At each moment of time only one operation can be active within a machine (unit).
3) Microtechnological operation is a finite sequence of elementary operations which constituent the contents of a technological operation, that is run continuously at one workplace. Within ISA-88 standard it is a phase that results in small changes in the properties of a product. Those steps can be run in parallel, in sequence or as a combination of two. Operator can't directly control the steps (start/pause/resume).
4) A Probabilistic technological process is a technological process that has probabilistic parameters of operation; a technological process with a structure that may change during its operation.

5) A Control system is a well-defined set of hardware-software means for control of a technological object, that makes it possible to collect readings of its state and to influence its operation in order to achieve the given goals.
6) Adaptive control is a set of methods and algorithms that allow synthesizing the control feedback connections that can change parameters (control structure) of the neuroregulator based on the control actions and external disturbances.
7) Automated control system of a technological process (ACSTP) is a complex of technical and software means that makes it possible for technological units to operate in automated mode based upon the chosen control criteria.

technological process
$:=$ [technological cycle]
$:=$ [is a sequence of interconnected operations, that is defined by technological documentation, directed at the object of process with purpose of producing the required output]
$:=$ [a set of technological operations $\{TCO_{ij}\}$, where $i, j = \overline{1, N}$, as well as the resources consumed by those operations]

probabilistic technological process
$:=$ [PTP]
$\subset$ *technological process*
$:=$ [technological process that has probabilistic parameters of operation]
$:=$ [a technological process with a structure that may change during its operation]

technological operation
$:=$ [TCO]
$\subset$ *technological process*
$:=$ [subset of a technological process, that is being run continuously at one workplace on one or more simultaneously processed or assembled products by one or more operators]

microtechnological operation
$:=$ [MTCO]
$\subset$ *technological operation*
$:=$ [finite sequence of elementary operations which constituent the contents of a technological operation, that is run continuously at one workplace]

III. PROBLEMS OF ADAPTIVE CONTROL OF PRODUCTION PROCESSES IN THE CONTEXT OF NEW GENERATION COMPUTER SYSTEMS DEVELOPMENT

Enterprise automation tools must be able to adapt to any changes in the production process itself with minimal costs and time delays. Such changes may include expansion or reduction in production volumes, changes in production nomenclature, replacement or changes of technological units, alteration of the overall production structure, changes of interactions between suppliers and consumers, changes of the legal acts and standards, as well as other unforeseen circumstances of different nature.

Analysis of the field in the sphere of the modern controlled production systems research demonstrates that the problem of determining the real-time operation parameters of such research objects emerges primarily in the cases of complex technical products production that requires high manufacturing precision and high labor productivity.

In such cases when solving a multicriteria control optimization problem high standards need to be applied to the algorithms of the operation of the production process, minimization of human factor impact on the technological production cycle operation quality, prevention of occurrence of technogenic emergencies. Such a case is typical for robotic production systems that operate under control of the hardware and software controller that administers the functioning of the technological cycle control system according to the given programs.

At the same time the arising emergency situations due to equipment failures, random external control actions, including human factor, lead to deviation of the operation parameters of the production system from the desired values, which leads to the necessity of their correction in real-time based on the neuroregulator models that operate within the hardware-software coupling means of the technological production cycle.

The existing special artificial intelligence models such as neural networks have unique properties and can be used as universal approximators that have a capability to generalize the data against which they were trained. Such features make it practical to use such models when solving complex problems in the domain of adaptive control.

The modern convergence tendencies in the sphere of intellectual systems development [1] requires the development of the appropriate software that would feature elements of cognitive abilities based on semantically compatible technologies of artificial intelligence. This sphere also includes the development of computer systems that are able to provide intellectualization of the processes of making analytical control decisions (which are directly related to adapting control processes for complex dynamic systems (technological objects) in real-time), building semantically compatible knowledge bases in the domain of dynamic systems operation analysis and optimization of the operation of complex control systems based upon them through open-source intellectual decision support systems development.

IV. BUILDING A MATHEMATICAL MODEL OF A PRODUCTION SYSTEM IN THE CONTEXT OF INDUSTRY 4.0

Implementation of Industry 4.0 concept at industrial enterprises is accompanied by creation of a unified ontological model of the production process. This model is the core of integrated information service for the company [13].

In order to allow a wide implementation of the artificial intelligence technologies for automating the company, all corporate knowledge must be transformed into the formal language for knowledge representation. Such knowledge may be obtained from the existing documentation that describes the enterprises' operation within the framework of accepted international standards.

It is necessary to transform each existing standard into a knowledge base based on the appropriate set of ontologies related to the standard. Such an approach allows to significantly automate the processes of standard development and its application.

As an example let us consider ***ISA-88*** standard [16] (the base standard for prescription production). Even though this standard is widely used by American and European companies (and is being actively introduced in Republic of Belarus) it has a number of flaws that are listed below. Authors' experiences with ISA-88 and ISA-95 have demonstrated the following problems related to versions of the standard (see [8]):

1) American version of standard – *ANSI/ISA-88.00.01-2010* – has been updated and is in its 3rd edition (as of 2010);
2) *ISA-88.00.02-2001* – includes data structures and guidelines of languages;
3) *ANSI/ISA-TR88.00.02-2015* – describes an implementation example of ANSI/ISA-88.00.01;
4) *ISA-88.00.03-2003* – an activity that describes the use of common site recipes with and across companies;
5) *ISA-TR88.0.03-1996* – shows possible recipe procedure presentation formats;
6) *ANSI/ISA-88.00.04-2006* – structure for the batch production records;
7) *ISA-TR88.95.01-2008* – describes how ISA-88 and ISA-95 can be used together;
8) At the same time, the European version approved in 1997 – *IEC 61512-1* – is based on the older version *ISA-88.01-1995*;
9) Russian version of the standard – *GOST R IEC 61512-1-2016* – is identical to *IEC 61512-1*, that is also outdated. Also it raises a number of questions related to the not very successful translation of the original English terms into Russian.

Another standard that is often used in the context of Industry 4.0 is ***ISA-95*** [17]. ***ISA-95*** is an industry standard for describing high level control systems. Its main purpose in to simplify the development of such systems, abstract from the hardware and provide a single interface to interact with ERP and MES layers. It consists of the following parts (see [8]):

1) *ANSI/ISA-95.00.01-2000*, Part 1: «Models and terminology» — it consists of standard terminology and object models that can be used to determine what information is exchanged;
2) *ANSI/ISA-95.00.02-2001*, Part 2: «Object Model Attributes» — it consists of attributes for each object defined in Part 1. Objects and attributes can be used to exchange information between different systems and can also be used as the basis for relational databases;
3) *ANSI/ISA-95.00.03-2005*, Part 3: «Models of Manufacturing Operations Management» — it focuses on Level 3 (Production/MES) functions and activities;
4) *ISA-95.00.04* Part 4: «Object models and attributes for Manufacturing Operations Management». The SP95 committee is yet developing this part of ISA-95. This technical specification defines an object model that determines the information exchanged between MES Activities (defined in Part 3 of ISA-95). The model and attributes of Part 4 form the basis for the design and implementation of interface standards, ensuring a flexible flow of cooperation and information exchange between various MES activities;
5) *ISA-95.00.05* Part 5: «Business to manufacturing transaction (B2M transactions)». Part 5 of ISA-95 is still in development. This technical specification defines operations among workplace and manufacturing automation structures that may be used along with Part 1 and Part 2 item models. Operations join and arrange the manufacturing items and activities described withinside the preceding a part of the standard. Such operations arise in any respect ranges withinside the organization, however the attention of this technical specification is at the interface among the organization and the management system;
6) *ISA-95.00.06* Part 6: «Transactions between Manufacturing Operations»;
7) *ISA-95.00.07* Part 7: «Model of Service Messages»;
8) *ISA-95.00.08* Part 8: «Profiles of Information Exchange».

Models help define boundaries between business and control systems. They help answer questions about which functions can perform which tasks and what information must be exchanged between applications.

The first phase of building a digital twin model requires embedding data at lower levels of production, such as production processes and equipment (see [15]). The connection with other software components that solve different tasks (acquiring, saving, displaying, analyzing data, etc.) should also be taken into account, but in general they form a digital twin (see [23]). The P&ID production scheme serves as the source of this data. Therefore the ISA 5.1 standard [18] has to work with the P&ID scheme and is widely used in control systems along with the ISA 88 standard to fully describe the lower production levels. This standard is useful when a reference to equipment is required in the chemical, petroleum, power generation, air conditioning, metal refining, and many other industries. The purpose of this standard is to establish a consistent method of naming instruments and instrumentation systems used for measurement and control. For this purpose, a designation system is presented that includes symbols and identification codes.

One of the important problems when implementing a standard at a company is the possibility of ambiguous interpretation of various parts of standard, as well as the necessity to constantly alter and improve this interpretation in such a way that it becomes closer to original. Moreover, there are specific features of implementing a standard at a particular company, the necessity to update the standard that is being used (because each standard constantly evolves) followed by changes to structure and organization of the company's activities to ensure compliance with the standard.

In order to build a mathematical model of a production system it is required to formalize the technological processes of this production system. The formalization of the mathematical models of the object under study and the control contour is based upon the results of authors' research in the area of simulating modeling of complex technical systems [2].

Traditionally two groups of technological processes are being considered:

- continuous;
- descrete.

The first group of technological processes is usually implemented during the production in real-time. These technological processes are a subject of an automated control system of a technological process (ACSTP). For example, ACSTP can be used to control the process of steelmaking, control the flow of raw materials into open-hearth furnaces and automatic pouring of metal into molds. The second group of technological processes is characterized by a graph structure of a technological cycle organization, that operates as set of interconnected operations $\{TCO_i\}$. Some TCO_i may in their turn consist of a set of microtechnological operations $\{MTCO_{ij}\}$.

Depending on how $\{TCO_i\}$ include $\{MTCO_{ij}\}$ the following types of technological processes can be identified:

- single-level processes, which consist of $\{MTCO_{ij}\}$ that can run in parallel or sequentially based on the graph structure that describes connections between $MTCO_{ij}$);
- hierarchical processes, that feature a main technological branch that is divided into several child-branches, that will then merge again; in this case as part of $MTCO_{ij}$ of any level there are operations of "splitting" of technological lines and operations of "merging" of technological lines;
- iterative, that feature child operations nested within the main operations; in this case the operation execution results at some nesting level are used to execute child technological branches.

Modeling of all types of technological processes is performed based on critical or average values of resource consumption. Probabilistic technological processes of the second and the third type are considered to be the most difficult to model.

When $MTCO_{ij}$ is running resources of the technological cycle are being spent. Based on the nature of resource consumption two groups of processes can be considered:

- deterministic processes (DTP) that have resources consumed based on critical or average values;
- probabilistic processes (PTP) that have some resources consumed in deterministic way (defined by lists of resources and their volumes) while other resources are being spent in a probabilistic way (defined by probability distribution functions for the resource consumption) by its $MTCO_{ij}$.

Some $MTCO_{ij}$ of a PTP may not only consume resources during operation but also perform control activities that change control variables U_s of the PTP.

During PTP's normal opearation each component of the U_s control variables set must be within acceptable ranges of minimal (U_s^-) and maximal (U_s^+) values. These changes in U_s values may also be of probabilistic nature. Some $MTCO_{ij}$ may alter control variables values in such a way that U_s are returned into acceptable ranges ($U_s^- \le U_s \le U_s^+$).

Let us consider a task of modeling reliability characteristics for the technological cycle hardware.

PTP uses in its operation technological units (machines) that may have various reliability characteristics. The technological units have some resource of operation that would gradually decrease depending on the time of active usage of the given unit. When a hardware unit reaches a threshold for this resource during active operation the probability of failure increases dramatically and therefore in a real world situation it is necessary to act in a timely manner and switch to a reserve unit (if possible) or perform maintenance in order to restore the unit's resource.

The moments of time at which a unit will fail are determined by probability distribution functions for the machine's operation time before failure. Units' failures may result in emergencies of different types that require quick reactions in order to eliminate their consequences, which may lead to the expenditure of material resources and time delays.

Reliability characteristics of hardware units are defined the following way [2]:

- moments of hardware failures are defined by the probability distribution function $F(\tau_{NOw})$ of normal operation for the appropriate unit; when the value is exceeded by the operation time a failure will occur;
- if a simple failure happens normal operation can be restored after an interval (τ_{ROw}) ;
- some failures may lead to a simple emergency with probability (P_{f1}) ; liquidating an emergency requires (τ_{EM1w}) additional time and (c_{EM1w}) of additonal costs to cover the restoration of normal operation;
- some failures may lead to a complex emergency with probability (P_{f2}) ; liquidating of such an emergency requires execution of a sequence of special technological operations; each of those operation may require additional time (τ_{liq}) and additional costs (c_{liq}) ; therefore liquidation of such a complex emergency may lead to operation time delay of $\sum \tau_{liq}$ and increases in costs of $\sum \tau_{liq}$.

A separate type of PTP can be considered where emergency may lead to stop of operation for the whole PTP. Such emergences are liquidated as the complex emergences but the whole TP operation halts until the liquidation is finished.

Thus project modeling of the PTP is a complex scientific problem due to the probabilistic nature of the resource consumption by $\{MTCO_{ij}\}$ and presence of equipment failures that may also be of probabilistic nature.

V. FORMALIZATION OF THE TECHNOLOGICAL CYCLE CONTROL CONTOUR BASED ON OSTIS TECHNOLOGY

In line with the knowledge domain ontology for the probabilistic technological processes, the technological production cycle means a sequence of actions and operations that result in some final (or semi-final for this stage) product.

The functional interaction between the components of the control complex and the operating in real-time technological production cycle is based on continuous monitoring of the equipment states and the control parameters through registers-indicators and means of technical coupling.

In order to build a robust semantically compatible intellectual system for control adaptation OSTIS Technology will be used as a base for the control complex. The system includes agents to address the tasks of interacting with the means of technical coupling and making control decisions.

In OSTIS Technology problem solvers are implemented based on multi-agent approach. According to this approach the solver is constructed as a set of agents, that are called sc-agents. All such agents share memory and may exchange data through special semantic structures (sc-texts). It is important to note that some agents may not be atomic (i.e. may consist of two or more sc-agents).

The full problems solver for the control task can be implemented as a decomposition of an abstract non-atomic sc-agent.

abstract non-atomic sc-agent of cycle recommendation system
⇒ *decomposition of abstract sc-agent**:
{• *abstract sc-agent of interaction with the observation system*
• *abstract sc-agent of forming recommendations*
• *abstract sc-agent of forming requests*
}

1) abstract sc-agent of interaction with the observation system -– is used to extract observations from the means of hardware-software coupling in the technological cycle; it initiates operation of agent for forming recommendations;
2) abstract sc-agent of forming recommendations — based on the received observations initializes controller operation in order to get recommendation for control actions;
3) abstract sc-agent of forming requests — based on the data received from the agent of forming recommendations forms requests for changing the control cariables of the PTP through the appropriate hardware-software means of coupling.

Agents of interaction with the observation system and forming requests must correspond with the technical system under consideration and allow communicating with the means of technical coupling.

When developing a control adaptation system within the task of building an ostis-system solver of the given structure an agent for forming recommendations based on the received observations must be created.

Construction of the controller used by the sc-agent of forming recommendations can be based on neural networks as well as other modern machine learning models and algorithms.

VI. DEVELOPING NEUROREGULATOR MODELS FOR ADAPTIVE CONTROL PROBLEMS

Several approaches may be proposed when considering the adaptive control problem:

1) direct control (controller modeling), when a neural network is trained on a database of existing "optimal"

signals (of an existing controller) [5] that lead to the desired trajectories in the phase space of the system and thus the neurocontroller for the control system is built [12]. Such a scheme is one of the most simple ones, but it has flaws such as a requirement to have a representative set of the existing physical controller statistics;

2) direct inverse control [4], in this case during modeling of the control contour operation the neurocontroller learns to reproduce a relation between the control signal at the current moment of time and observations of the control object at the next moment of time [6] [7];
3) Schemes may be proposed where the neurocontroller is built using reinforcement learning, particularly:
   - neurocontroller trained through reinforcement learning procedure for a task of finding an optimal trajectory (optimal in some «geometrical» sense) in the phase space of the control system states [3] [4] [9];
   - neurocontroller trained through reinforcement learning procedure for a task of implicit optimal trajectory search when some estimation of the control quality R is used [10] [11].

Since the problem of selecting an appropriate neural network structure for the particular task is in each case complex and difficult to formalize, it may be useful to consider application of the evolutional methods for its automation. [14] .

When controller modeling is used the neurocontroller is trained in such a way that it would be able to reasonably generalize over the collected data of the control process for the technological cycle. In this case from the machine learning theory point of view, supervised learning occurs, when the collected data will be used as pairs of desired input and output (control signals) vectors of the controller. From the point of view of the dynamical systems theory a phase space of the technological process control system is an environment where a decision about control actions must be made based on the observed state. And therefore the process of neural network training may be viewed as a process of learning the correct trajectories in the phase space that correspond to optimal controls.

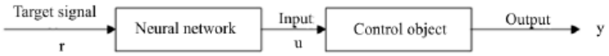

Figure 1. Direct control scheme

Training process with inverse scheme is similar from the machine learning point of view. The difference is that the desired observation signals of the control object are used as a source for building the loss function that would be optimized.

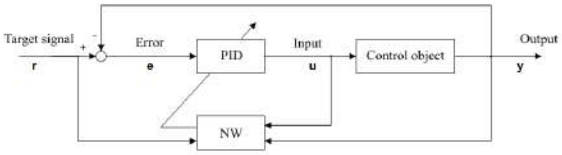

Figure 2. An example of a scheme with inverse control

The schemes where reinforcement learning is implemented have a potential for building an effective controller due to the presence of an exploratory element in them when searching for a control strategy. This may have a positive effect when solving problems with complex structure of the control decisions.

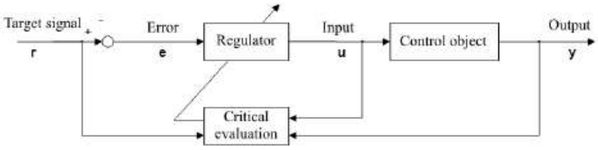

Figure 3. Reinforcement learning scheme

Let us consider some functional R for estimating the quality of the control (estimation of the quality of the control policy (cotrol actions selection by agent (control system)) π) that is calculated during the time period of the TP operation $[0, t]$. (For example this functional may «reward» for lowering the production costs and «penalize» for equipment downtime, occurence of hardware failures or emergencies).

Decision making in this case can be managed by a neural network (agent operating under the neural network control).

When agent performs certain actions this leads to some sort of trajectory being built in the phase space (in this context the control construction is considered to be a trajectory construction in the phase space of the technological process control system states).

The problem of search for an optimal trajectory in the phase space of the system, thus is equivalent to maximizing R (at this moment of time and at the future moments - meaning that the controller for the technological cycle is required to produce such an action selection policy π, that would maximize the estimate for control quality R).

Application of reinforcement learning methods assumes the existence of environment, in which a critical evaluation of agent's actions happens. An environment in which an agent operates in the context of the technological cycle control is the system of control of technological production cycle. This environment makes it available for agent's observations signals of registers indicating the equipment states and control parameters. Based on the agent's decisions the decision making system forms requests for altering the control parameters.

For example reinforcement learning schemes based on Q-learning and policy gradient can be implemented to solve the task of searching for an optimal hardware maintenance strategy for the technological cycle of production [10] [11]. In this case neuroregulators are trained in a simulation that models technological cycle operation with given hardware reliability characteristics and structure, and R functional that is used to estimate model's performance is constructed in such a way that it would satisfy system user's requirements (e.g. costs minimization while avoiding serious hardware failures).

As another example to illustrate an adaptive control problem solved by neural network methods let us consider a temperature stabilization task during the operation of a pasteurizer machine. Pasteurizer is a machine for heat treatment and cooling of milk products in a continuous thin-layer closed flow. For automating the temperature regime adjustment the pasteurizer includes a control system based on an industrial controller. Quality of the final product directly depends upon the implemented algorithms.

The main reasons for temperature fluctuations t_{mn} during milk heating are flow G_m volatility of the product, temperature t_0 fluctuations in the source milk, flow G_p changes n steam that exist because of pressure P_p fluctuations, change in heat transfer coefficient K because of protein deposits on heat transfer surfaces. To stabilize the temperature t_{mn} of milk heating mainly steam flow G_p is controlled. It is controlled by a controlled valve.

A neural netwok based scheme with a proportional–integral–derivative (PID) regulator can be proposed to solve this task. The general structure of the self-adjusting neuro-PID regulator is shown on figure. Neural network outputs are proportional (K_P), integral (K_I), derivative (K_D) coefficients.

In descrete time PID-regulator can be described using the following formula:

$$u_n = u_{n-1} + K_p(e_n - e_{n-1}) + K_I e_n + K_D(e_n - 2e_{n-2} + e_{n-2}),$$

where K_P, K_I and K_D — proportional, integral and derivative coefficients respectively, u_n defines the output of the control object at moment $t = nT_0$ and e_n — error between desired output value r_n and the real one, meaning

$$e_n = r_n - y_n,$$

where T_0 defines a singular time interval.

To adjust K_P, K_I and K_D during the operation a 3-layer perceptron will be used. Each layer has N_1, N_2 and N_3 neurons respectively. The number of neurons is selected based on the researcher's expertise and complexity of the control object, N_3 equals 3 - number of coefficients in PID. In order to use the backpropagation algorithm a function E must be chosen for minimization. Control error function e_n is used at moment nT_0.

$$E_n = \frac{e_n^2}{2}$$

For error accumulation the previous data is saved – $E_{n-p}, ..., E_{n-2}, E_{n-1}, E_n$, where p defines the number of previously saved data points for neural network training.

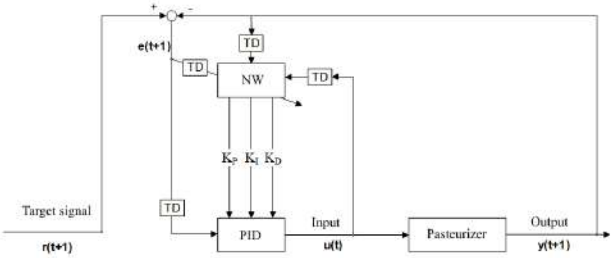

Figure 4. Neuro-PID regulator, TD means time-delay elements

Therefore approaches based on the modern machine learning algorithms such as neural network allow solving complex control adaptation tasks for the technological processes and can be used as a base for constructing problem solvers for the appropriate ostis-systems.

VII. CONCLUSION

Lately algorithms and methods are being actively developed and improved for the class of applied problems related to control of robotic production when external random influences on the control object are present.

In this paper a procedure is being proposed for synthesizing feedback control connections for technological production cycle and adaptation methods are proposed based on formalization within the framework of OSTIS Ecosystem and building artificial neural network models for solving applied tasks of control optimization for complex technological systems.

The obtained results make it possible to develop new hybrid intellectual computer systems with the purpose of solving a wide class of applied problems of control adaptation in real-time for technological objects using ostis-systems and technical means of hardware-software coupling of the control object.

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Система адаптивного управления технологическим циклом производства в рамках Экосистемы OSTIS

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В настоящей работе предлагается подход к построению гибридной интеллектуальной компьютерной системы адаптивного управления технологическим циклом производства в виде решателя соответствующей ostis-системы на основе онтологии предметной области «технологические процессы производства с вероятностными характеристиками». Основой для создания решателя системы служит идея разработки и использования математических моделей нейросетевых регуляторов для решения задач оптимизации управления. Такая реализация позволяет обеспечить возможность интеграции предлагаемого решения с другими разработками, программными средствами предприятия для обеспечения построения интеллектуальных систем автоматизированного управления, рекомендательных систем и систем поддержки принятия решений, систем информационного обеспечения персонала предприятия.

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