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Original article

# The concept of an automated control system for the production process of robotic complexes

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***Abstract.*** This article presents the concept of an automated control system for the production process of robotic complexes. The diagram of the control system for the production process of robotic complexes and the structure of the interaction of agents in the described production model are shown. It is assumed that AI based on multi-agent neurocognitive architectures will be used as an intelligent decision-making system in the control system. Such a model will make it possible to simulate complex processes of interaction both between organizational nodes and between external actors. In the future, the system will be able to provide adequate planning at the organizational level, taking into account all available factors.

***Keywords:*** robotics, production, intelligent systems, multiagent algorithms, automated control systems

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## INTRODUCTION

The current level of industrial development (with the already established definition of “Industry 4.0” [1]) involves not only the transition to new technologies, but also taking into account the digitalization and intellectualization of modern society, as well as a shift towards individual production. That is, modern production must constantly introduce new technologies both in the production process itself and at the management level for successful development in an extremely competitive environment. Actively implemented approaches include the use of the Internet of things and cyber-physical systems, intelligent processing of large amounts of data, and personalization of production [2].

At the same time, the development of robotic devices and complexes for various purposes, as one of the most technologically advanced areas of production, clearly implies the possibility of effective implementation of modern control automation systems. The development of an autonomous robot involves the creation of design and mechatronic solutions, as well as the development of electronics and software for it (Fig. 1).

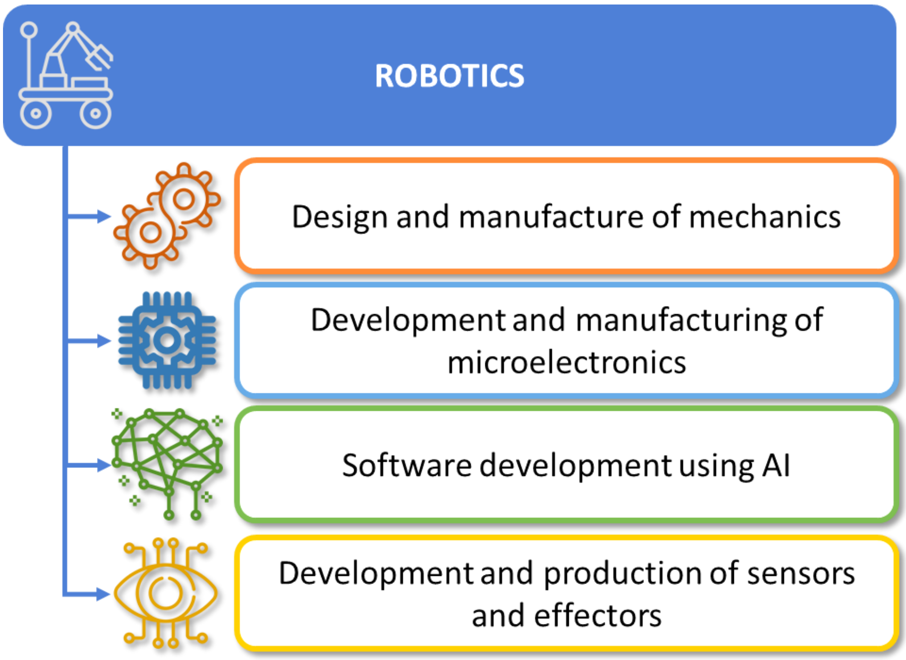


***Fig. 1.*** *Elements of manufacturing robotic devices*

The complexity of organizing such production is noticeably higher than in other, more established areas of activity. Based on the above mentioned, the task of developing the concept of an intelligent control system for the production of autonomous robots can be considered relevant.

## APPLICATION OF INTELLIGENT DECISION-MAKING SYSTEMS IN PRODUCTION PROCESS MANAGEMENT

Technologies related to Industry 4.0 have been successfully introduced into modern production for quite a long time. For example, Internet of Things (IoT) technologies find application in automating the collection and processing of information from production sites [3]. For example, the use of wireless sensor networks can significantly reduce the cost of laying cables in a building, which often allows significant savings despite the high cost of the sensors themselves. At the same time, many of the sensors used often have on-board data pre-processing systems, which makes it possible to relieve the data transmission network and promptly respond to a number of emergency situations at the place of their recording. In addition, the authors proposed a service-oriented architecture for IoT systems in manufacturing (Fig. 2). At higher levels of the architecture, the received data is processed using big data technologies and artificial neural networks.

It is worth noting that there is significant experience in implementing intelligent data analysis systems in production processes. For example, the Internet of things together with expert systems were used to develop an additive manufacturing system that can significantly reduce the load on management and ensure the fastest possible transition from the proposed model of the device being developed to its physical implementation [4]. Pre-trained artificial neural networks were used to determine the stages of production and equipment control based on the input model (obtained as data from a computer-aided design system).

Intelligent systems based on neural networks are also used in the task of predicting possible equipment downtime [5]. This will optimize the process of preventive maintenance of used equipment and reduce the risks of unexpected downtime, leading to significant financial and reputational losses for the organization. At the same time, the use of data obtained directly from the enterprise sensor network for training and testing neural networks allowed the authors to achieve a high level of forecasting and minimization of equipment maintenance costs using the example of a forestry enterprise.

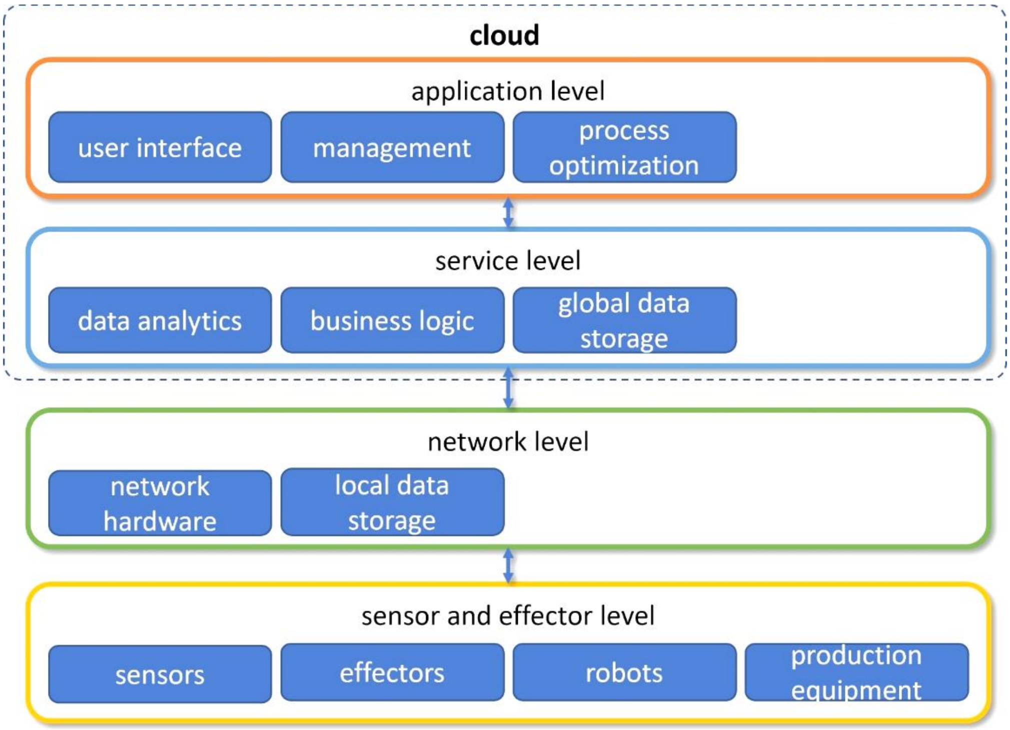


***Fig. 2.*** *Service-oriented architecture for IoT systems*

A rather interesting example of the use of ultra-precise neural networks is described in [6], where the authors proposed a system for automating quality control in the production of microelectronics products through the use of an optical camera. The presented neural network architecture, using data from the camera, made it possible to determine several types of defects or their absence) in the process of placing capacitors on an electronic board. Due to the sufficiently large volume of the training sample, which can be obtained in production and under controlled shooting conditions, the neural network showed a fairly high level of accuracy in determining the defect. Such solutions will minimize the amount of defects without the need for manual control of the entire flow of manufactured products, which is extremely important for large-scale production.

A similar approach was used to identify screws and nuts on assembled products [7]. The work compared the architectures of convolutional neural networks (AlexNet, Visual Geometric Group, and ResNet). A fairly accurate class determination is achieved using the ResNet architecture with 300 training epochs. In this case, even similar objects (nuts of different types) are distinguished with an accuracy of above 90%. It is worth noting that there are neural network architectures (for example, Yolo v9), that, in theory could show better results but were not considered by the authors of this article.

A separate area is the modeling of production processes, including through the use of intelligent systems. For example, already established virtual reality technologies can be used to simulate production [8], which is especially interesting at the stage of production planning, product design, and employee training. To optimize production chains, genetic algorithms are also applicable, allowing you to select a suboptimal set of operations that allow you to achieve your goal (for example, to produce a tedious device at minimal cost) [9]. In addition, ontology-based finite state machine modeling can provide optimization of control systems for production robots [10]. Classical mathematical methods (for example, the finite element method) in modeling both the products themselves and production processes in general remain no less promising [11].

## CONCEPT OF A CONTROL SYSTEM FOR THE PRODUCTION PROCESS OF ROBOTIC COMPLEXES

In the case of the production of autonomous robots, all the technologies described above are applicable. At the same time, this study aims to develop the concept of an intelligent production management system, using the example of the development of autonomous robots. In particular, intelligent manufacturing control is of interest as part of the development and implementation of projects related to autonomous robots. For example, as part of research at the Kaliningrad Scientific Center of the Russian Academy of Sciences, a robot for protecting crops [12] and a platform for monitoring archaeological sites are being developed [13].

The production process control system for robotic complexes must ensure data collection, modeling of production processes, and generation of a work plan. The control system diagram is shown in Fig. 3. Data collection should be carried out not only from the sensor network in production, but also from external data sources that allow analyzing the condition of equipment, supply chains, general indicators of the enterprise and the condition of employees. Also, analysis of data from open registers (databases, websites, open reports) will allow us to model the economic indicators of counterparties, competitors and the entire region as a whole. This data is used by an intelligent decision-making system to model the current state of production and the market and the dynamics of their development. The goal-setting module involves the user selecting goals for management (and maximizing benefits may not be the only or even the highest priority goal). The resulting models are used to select a suboptimal trajectory of enterprise development and generate a behavior plan that influences the actors of the organization (machines, employees, departments) and external counterparties (distributors and counterparties).

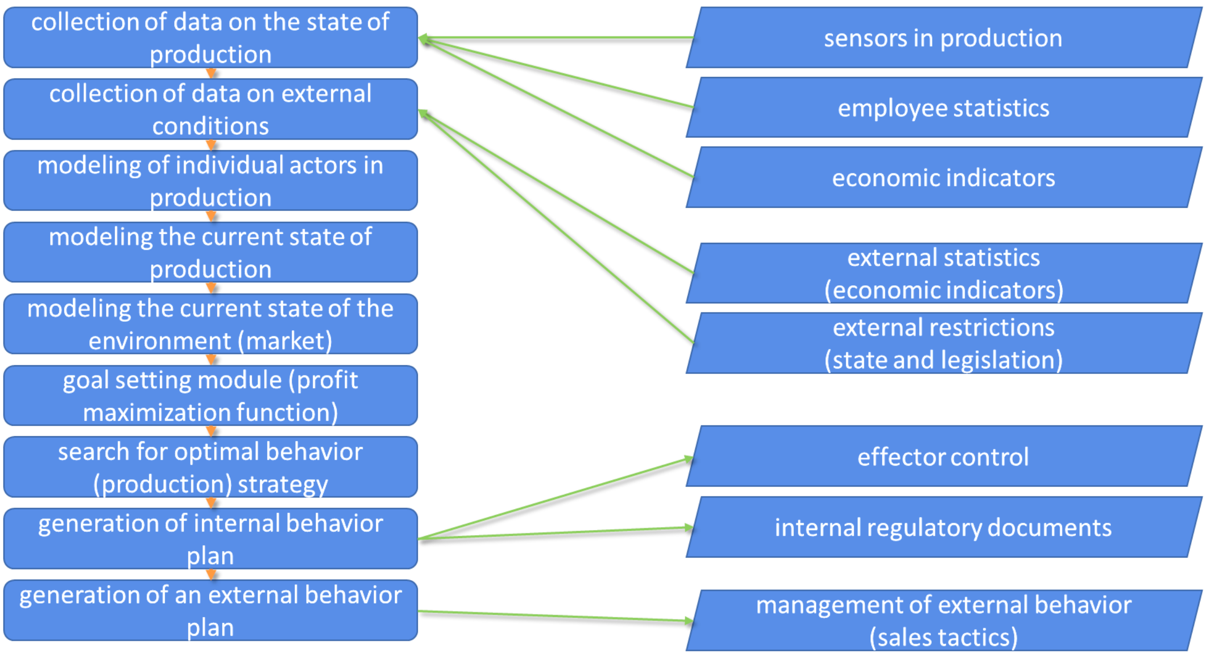


***Fig. 3.*** *Diagram of the control system for the production process of robotic complexes*

As the basis of an intelligent decision-making system, an artificial intelligence formalism based on multi-agent neurocognitive architectures is considered, which makes it possible to simulate the interactions of many neuron agents [14]. A neuron in such a model has its own target function of maximizing internal energy and can dynamically enter into contracts, exchange information and energy [15]. Such models, unlike classical neural networks, are theoretically capable of self-learning and do not require large training samples. In the future, the use of multi-agent architectures in decision-making systems will make it possible to build ontologies responsible for the subject area (for example, for the production of complex equipment), predict external conditions, model the process of developing and selling goods, and select optimal solutions for production management.

In this case, the process control system model includes a number of separate models: the production agent, the external agent and the directly produced product. The interaction diagram of agents in the control model is shown in Fig. 4., Fig. 5 shows a more detailed diagram of the structure of the simulated agents.

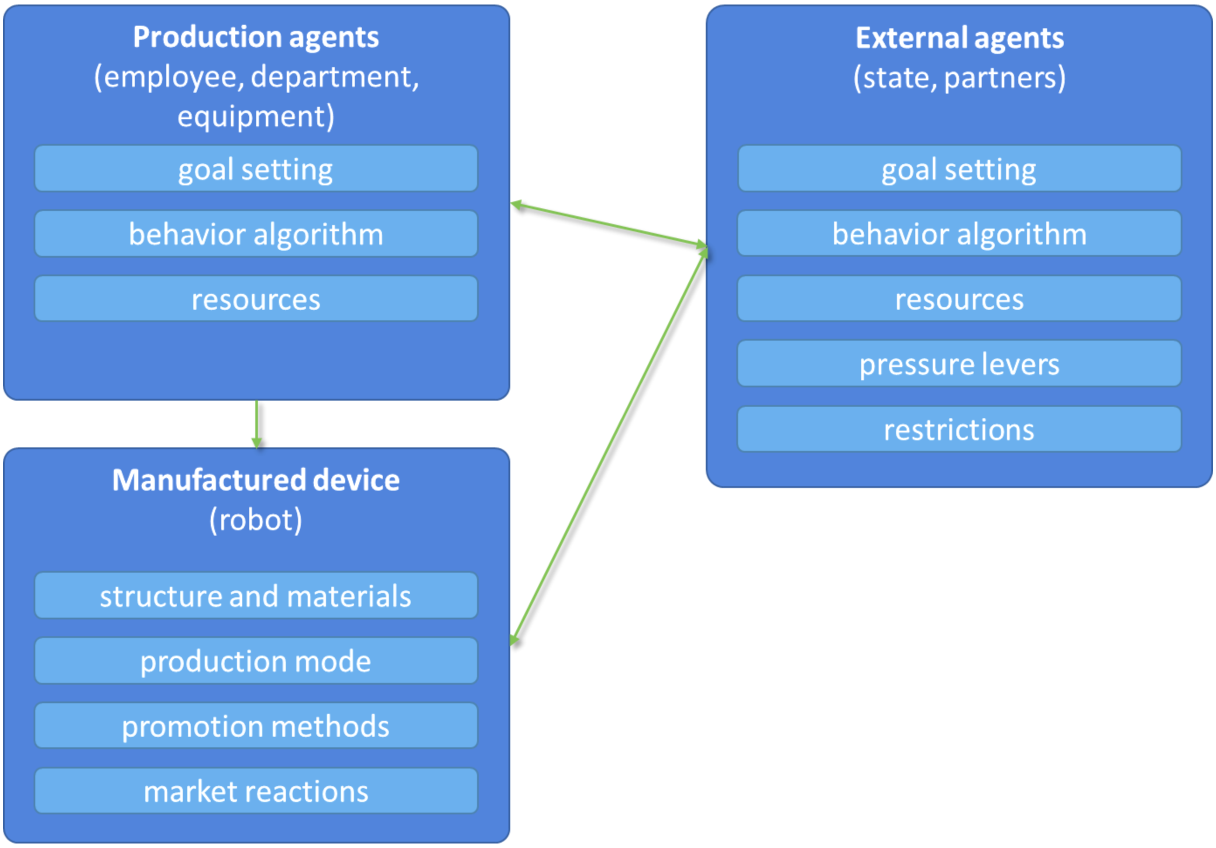


***Fig. 4.*** *Scheme of interaction between agents in the model for controlling the production process of robotic complexes*

A production agent (an employee, a piece of equipment or a department of an enterprise) consists of its own goal-setting system (not necessarily related to the overall goal of the enterprise) and a behavior algorithm. In addition, each such agent has a different set of resources available to it, the exchange of which ensures the operation of production chains. The external agents here are the state, buyers, partners and competitors. External agents may have the ability to limit the work of production agents and have available leverage, that is, the possibility of production influencing them.

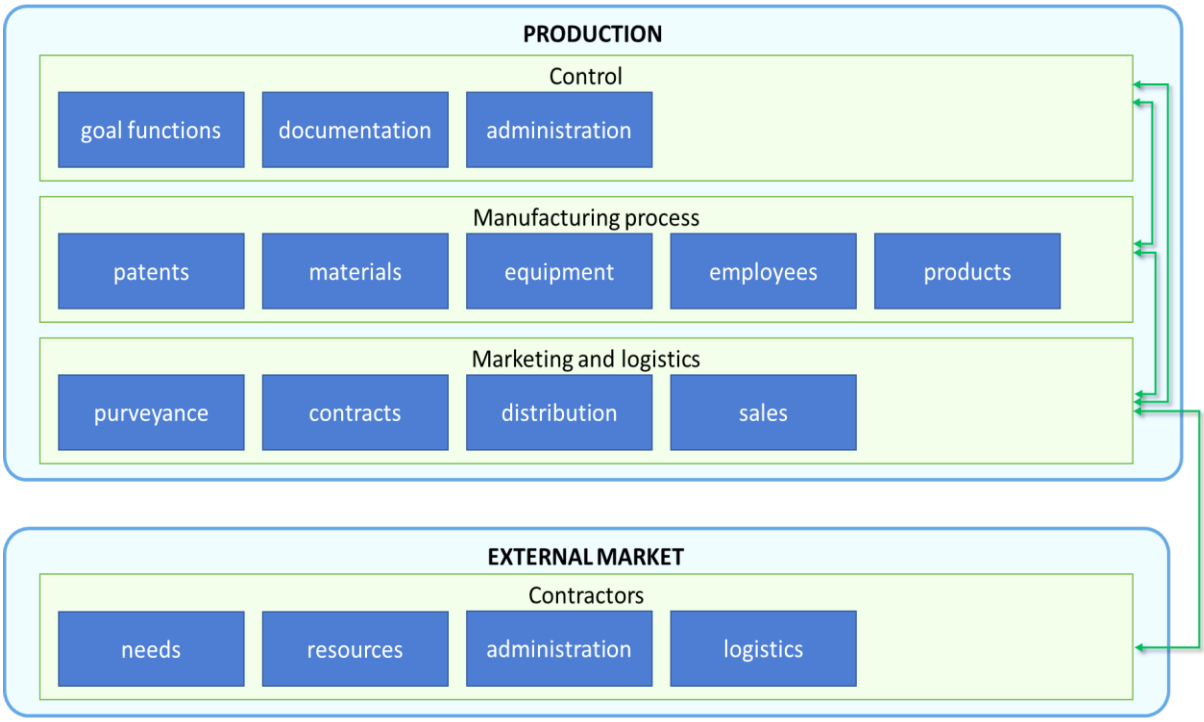


***Fig. 5.*** *Model of production of robotic complexes*

The formalism used assumes recursive models, that is, the agents being modeled can consist of other agents. For example, the production of robotic products itself consists of multiple agents, including a control system, a production chain and a support system. Each agent is modeled by one or more neurons and can exchange resources and messages with all available counterparties. Such a model will make it possible to simulate complex processes of interaction both between organizational nodes and between external actors.

## CONCLUSIONS

The presented concept of an intelligent control system for the production process of robotic complexes, which involves the use of multi-agent neurocognitive architectures for a decision-making system. For the management system being developed, it is planned to collect data both from a sensor network in production and from external data sources that allow analyzing the condition of equipment, supply chains, general indicators of the enterprise and the condition of employees. The data obtained will be used to create a multi-agent model designed to represent the current state of the organization and its external counterparties, as well as to predict the dynamics of their development. In the future, such a control system will allow for the automation of fairly complex and technologically advanced production, taking into account both technological chains and the external economic situation and goal setting of management.

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