Intelligent Control of Industrial Processes

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Abstract: The paper analyzes the problems of intelligent production control subject to world economy trends. It discusses the evolution of the problem of integrated plant floor and plant logistics control and overviews the state-of-the-art control theory methods and the ways to apply them in production control.

Keywords: Intellectual control, Intelligent control, Network control, Organizational control, Unified control, Model-based predictive control, Knowledge-based models, Data mining

1. INTRODUCTION

Intelligent control of production processes is a rapidly growing field of research with a promising potential of theoretical results and applications in both integrated production control systems and specialized control systems at various plant levels.

Control theory and methods show a clear trend to further convergence with artificial intelligence (AI) techniques. This is happening against the background of the increasing penetration of information and control technologies into various fields of human activities. In particular, the science intensity of production control is increasing in the “knowledge economy”.

Much as the political weight of a state, company’s compatibility is increasingly determined not only by the availability of material, energy, and financial resources but by intensive employment of intelligent resources as well. High-tech product does not obey matter and energy conservation laws, has no physical limits and its buildup increases the benefits of the related resources, products and services, also in planning, management, and control (Velikhov et al., 2007). Science intensity of products has been growing: by 2 orders of magnitude per 1 kg of weight for vehicles, 4 orders for aircraft, and 6 orders for VLSI circuits as against their material cost. The cost of avionics may amount up to 60% of a military airplane’s price.

Apparently, the success of production modernization depends, in particular, on the institutional environment in the country. Innovation management is an important part of a national economic policy in market-economy countries. For example, the overcoming of innovation management challenges, quality development, standardization, informatization programs are by 50% or more sponsored by USA government, because they lie beyond the scope of any specific industry or territory. The government has created the preferential tax and crediting systems, public financing of innovative design, effective antimonopoly law, public grant system for R&D and scientific information.

The term *Creative Economy* (Howkins, 2001) has been gaining popularity within the research community. A lot of publications appeared, and international conferences are being convened (Tairan and Florida, 2006). This economic development stage follows such ones as:

- postindustrial, featuring the prevailing development of human services
- informational, where the economic development is driven mainly by information systems and technologies
- knowledge economy, where intangible assets and intellectual property play the key role.

At the present-day creative stage of economic development, information and knowledge generate creative ideas, whose implementation (innovations) result in significant benefits within the global system. Specific economic development models may be utterly different, like, e.g., in China as against European Union countries.

The switch from cost management strategy to result management strategy based on project management is also apparent. In developed countries, national scientific and technological development strategies have been created. National institutes for development and state-private partnership are evolving, which contribute to national industry, science, and education embedding into the global labor division system created by knowledge economy leaders. The predominance of national companies or industries in the world market becomes the criterion of success.

By *control intellectualization* one understands today the process of increasing automation coverage and extending its application scope combined with ensuring the guaranteed control quality, in particular, with respect to such criteria as cost-effectiveness, reliability, durability, etc.

Computer technologies play the paramount role in the automation of human individual's professional activities and labor productivity increase. The basic trends in this area as per the viewpoint of key analysts (Gartner, Inc., 2008) look as follows:

- Virtualization and fabric computing
- Cloud computing and web platforms
- Web mashups
- Ubiquitous computing
- Contextual computing
- Augmented reality.

Low-power electronics, high resolution LCD screens, mobile and wireless communicators, positioning systems (GNSS, UWB, ultrasonic) make the framework of ubiquitous computing in the organizational and technological provision of networked manufacturing instead of conveyor lines. Instead of tailoring commercial solutions to custom requirements, the strategy of product multi-functionality ("Swiss army knife") under decreasing product lifecycle is gaining popularity (Vassilyev and Sabitov, 2012).

Ubiquitous and pro-active computing open up a new era of production computerization. As the PCs in 1970s-80s, wireless systems today increasingly overcome the skepticism of industrial users. More attention is paid to MODELWARE (models for control) and USEWARE (HMI).

As far as human cognitive and sensorimotor abilities have not changed much over the several recent millennia, the new generation control systems should focus on the human individual and his abilities without requiring significant adjustment of these abilities to any technologies (such adjustment looks hardly attainable and not at all necessary).

This picture is supplemented by the fact that the philosophy of automated control systems as computer-integrated manufacturing of the 1980s with its unmanned ideal has not been implemented so far because of the extreme complexity of effective planning and management systems for present-day production complexes. The pioneer philosophy of the 1990s is *lean production* (Toyota) based on network (rather than hierarchical) organization of cooperating self-organizing work teams instead of conveyors with strictly regulated personal responsibility.

The key attributes of the present-day production innovativeness (along with the degree of scientific and technical novelty determined by intellectual property including innovations in control techniques) are technological advantages and application benefits. Instead of attaining near-term control goals, new tasks arise, which should be accomplished under possible quick correction of conditions and constraints and prediction of situation evolution scenarios rather than single factors.

In the innovative modernization environment, the success will be determined by the following:

- Model development and control decision generation as well as result verification and analysis in control systems of production complexes should be done subject to the information (both historical and real-time) about the operation of production complex's elements, that is, the control should be executed on the basis of the *unified information space*.
- Control, identification, and simulation algorithms should rest on the knowledge generated and updated on the basis of process data analysis in the form of revealed regularities.

  Algorithmization of the switch from observation to prediction has been running under various titles: empirical prediction (EP), pattern recognition (PR), machine learning (ML), intelligent analysis of data (IAD), data mining (DM), cognitive computation (CC), etc. (Finn, 2004)
- At each moment, a certain strategy comprising possible changes of not only the parameters but the system structure as well should be implemented instead of a specific control algorithm.

One should allow for the increasing network control trend both for control system and communication channels, as well as the novelty of the arising multilevel control tasks. This promotes intensive development of network, multi-modal, group and multi-agent methods for production process control.

2. PRODUCTION PROCESS CONTROL SYSTEMS: STATE-OF-THE-ART SOLUTIONS

Competitive advantages in the present day turbulent market look hardly attainable without ensuring maximum possible information transparency and making optimal managerial decisions. Production process control should be optimized in a flexible and integrated manner, i.e., the optimization should comprise all business processes: production planning and resource management, operative-logistic production control, process control and marketing.

The systems comprising the full production cycle are listed below:

ERP – Enterprise Resource Planning

EAM – Enterprise Asset Management

APS – Advanced Planning and Scheduling

SSM – Sales and Service Management

CRM – Customer Relationship Management

SCM – Supply Chain Management

MOM – Manufacturing Operations Management

APC – Advanced Process Control

P&PE – Product and Process Engineering

MES – Manufacturing Execution Systems

LIMS – Laboratory Information Management Systems

DCS – Distributed Control System

SCADA – Supervisory Control and Data Acquisition

Industrial PLC – Programmable Logic Controller.

It seemed obvious in 1980s-90s that the integrated interaction of these systems or their functional fragments would provide comprehensive real-time surveillance of all problem areas and eventually improve production process efficiency as a whole.

The diagram in Fig. 1 shows the segmentation of production control.

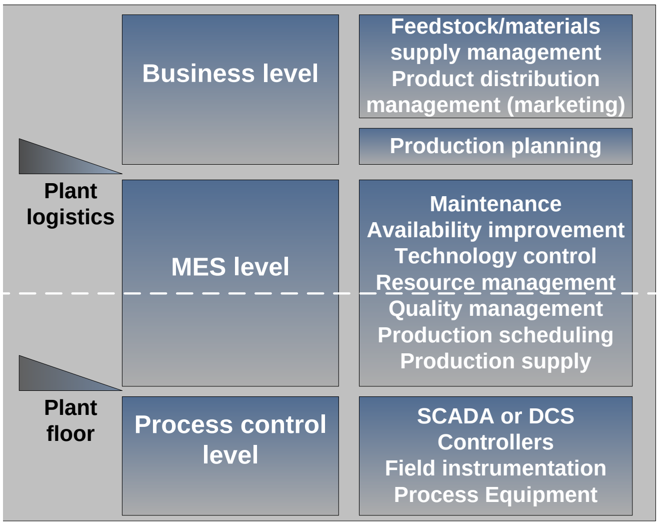

Fig. 1. Production control segmentation

The concept of *computerized integrated manufacturing*, which presumed not only the employment of computer technologies for process and operations automation but also the development of an integrated information system to control the production as a whole was offered (Mizyun, 2011). It became clear already then that informational integration of process (plant floor) and business levels is hard to attain without creating plant's unified information space.

Today this does not look enough – multifunctional architecture is needed for an integrated modular control system with specific requirements to its functions (rather than to hardware components), validation of requirements, implementation and verification, as, e.g., in integrated modular avionics.

However, a number of challenges were detected on the path to integrated production control systems. The first one seemed a most difficult but surmountable: no industrial automation market participant could offer products or services covering the whole range of control decisions (Bakhtadze et al., 2007). Control engineers were mainly updating hard-/software platforms of legacy systems or equipping new plants. On the other hand industrial ERP vendors had not enough expertise in plant floor automation because their products were focused mainly on accounting, finance and documentation management.

Moreover, the development of the unified information space required a special approach for specific enterprises. Information Control Systems at various production levels operated with vast volumes of heterogeneous data.

Despite significant advances in creating hi-tech hard-/software such as high-capacity data storages, visualization tools, situation monitoring and decision-making support tools, corporate databases, etc., more challenges had to be overcome for developing a unified information-control structure. First and foremost is the lack of correct data exchange between heterogeneous applications that could ensure reliable mobile integration of all subsystems. Also, the standards meeting new realities had to be developed.

Today, one can assert that the unified information space (Yakovis, 2013) does exist at a number of industrial enterprises and companies, in particular where corporate databases, monitoring systems, and DCS are available. For example, in the Russian DCS market such internationally acknowledged vendors as Emerson, Honeywell, Invensys, Siemens and Yokogawa are among the most popular. Their users are typically major plants. For small plants, a real challenge is posed by the prevalence of IT development rate over the equipment renewal rate that may be caused by purely commercial priorities. The answers to these challenges are standardization, middleware and global industrial servers, cloud technologies.

Still, it seems too early to speak about integrated control systems for both production levels (plant floor and plant logistics) altogether. As to production management, the market offers a number of systems integrating the control at various layers of plant logistics level. Analysts argue about the *controlling* as a special type of financial and economic activity of plant management. It is used for making short-term and strategic decisions subject to the whole plant's current status.

Process automation for various plants (even manufacturing the same product) shows individual features where unified solutions are hardly applicable. The same about design processes (CAD): for each enterprise, especially in instrument-making and machine-building, automation and control require individual approaches. Only the control of design of specific types of products may be generic in such systems.

Today, the combination (based on a unified monitoring system) of ERP, process control, CAD, supervisory control and MES make some kind of integrated production control systems with MES as a core.

Plant's unified information space enables not only the monitoring of production status but the operation of software aimed at various tasks: analysis, prediction, control, etc. (Bakhtadze et al., 2008). Algorithms and models can be adjusted in real time using both on-line data, including other process models or their fragments, as well as historical data. Software systems aimed at model design and tuning based on real-time data are called *inferential models*, or *soft sensors* (Albertos and Goodwin, 2002).

Typically, the term “soft sensor” is related with the plant floor. In process operations, inferential models describe the relationship between a process variable (typically, a product quality), which cannot be measured at the plant directly, with other process variables measured directly (Kern, 2007). Using real-time models for control at higher production levels looks reasonable, but the correct implementation of such approach requires the revision of the whole of integrated control methodology.

In recent years, model(-based) predictive control (MPC) became the most popular tool for addressing strongly interrelated multi-variable processes with a lot of constraints and big dead times (Qin and Badgwell, 2003). MPC is based on using a pre-designed process model in the control loop. A wider term Advanced Process Control (APC) is well-known; this comprises MPC as well as some other control technologies such as traditional (non-model-based) advanced controls (TAC, also called advanced regulatory controls – ARC), soft sensors, adaptive regulatory controllers, etc. Soft sensors play a key role in most of MPC solutions, as they provide the only cost-effective tool for on-line control of product qualities.

In 1970s, a concept of a process control system with an identifier in the control loop was developed. Such control systems were named “Automatic Systems with Identifier” (ASI; Rajbman, 1976). The model in such systems enables real-time adaptive parameter tuning. Industry first ASI was successfully implemented in mid 70s at a tube-rolling mill.

Process model building for continuous and semi-continuous (batch) processes requires parameter identification based on small samples. In such case, the choice of identification algorithms should be based on the time to steady state in the identifier and, moreover, low sensitivity to the initial estimate accuracy. These conditions along with the quasi-stationarity requirements hamper the implementation of such systems (Bunich, 2005).

High reliability is an important requirement for many critical applications. High capacity of such plants implies significant losses in case of failures. In some cases, insufficient information about the process requires robust control that ensures plant operation within constraints (Torgashov, 2005). Therefore, further investigating the capabilities of robust control theory and techniques in process control systems looks promising.

Now we return to the 2nd global challenge on the way to integrated production control systems. Tightening requirements in speed, accuracy and controllability under uncertainty conditions and various types of disturbances in control systems demonstrate the limitations of traditional approaches to automatic control system design. The attempts to apply “black box” approach for controlling complex multivariate plants were unsuccessful. The results of massive R&D are embodied mainly in systems of more or less scanty functionality with add-ins implementing various heuristic approaches.

The capabilities of classical artificial intelligence techniques are insufficient for handling a number of process control tasks as well as supervisory production control. For most of such techniques, it is typical that human intelligence serves as a prototype for developing an artificial one. However, the application of the results of further research in the field of AI shows that some approaches not underpinned by human mental architecture look more successful in certain tasks as against the abilities of human mind.

Both academia and industry came to conclusion that full automation of an industrial plant as of a socio-technical system should rest on an utterly different basis. A new methodological approach (by now, appealing to the participation of human intelligence in production control) effective in uncertainty and subsystem failure conditions is required. Mechanisms for timely changing of operation targets, quality criteria and constraints are needed (Popper, 1992, Gabbay and Smets, 2000).

3. INTELLIGENT CONTROL

To develop a new platform for integrated control of production process as a whole, we address the available bank of control theory results.

Along with automatic control under multicriteriality, uncertainty and risk conditions, which showed significant advances in the recent years, intelligent control techniques is making great strides. Under *intelligent control* (Vassilyev and Sabitov, 2012) we understand the capability of a hard-/software system to automatic development of control actions based on formalized expert knowledge and experience, mathematical and informational modeling to attain a target set by a human individual. This definition refers to control systems at both plant floor and plant logistics levels.

Intellectual control techniques is aimed at the automation of target setting as well as a real-time revision of quality criteria and constraints (Vassilyev and Sabitov, 2012, Vassilyev et al., 2000a, Finn, 2009, Anshakov and Gerdely, 2010, Benthem, 2007).

Intelligent and intellectual control (Fig. 2) combined with control hardware miniaturization, decentralized control in multi-agent systems and present-day computer technologies underlie state-of-the-art production control systems.

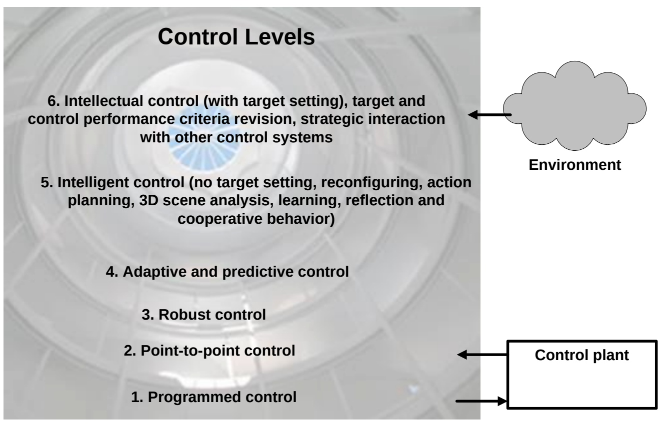

Fig. 2. Control level hierarchy

Multi-agent systems (MAS) exemplify the application of intellectual control methods and concepts. The hierarchical structure of MAS agents at a certain extent correlates with control concept and level hierarchy shown in Fig. 2.

At the lower MAS levels, such as stabilization, etc., point-to-point, robust and adaptive control principles are used; intelligent control occupies tactical and strategic levels, while intellectual control with target setting (actually used today only in interactive man-machine systems) lie on strategic and upper levels.

For intellectual control level, internal sub-hierarchy (Fig. 3) is often typical, e.g., the combination of neuro-reactive, logic-reactive (with production rules and perhaps with situation proximity estimation procedure) and logical levels of intellectual control (Vassilyev, et al. 2003).

Intellectual control tools are compared in Fig. 3.

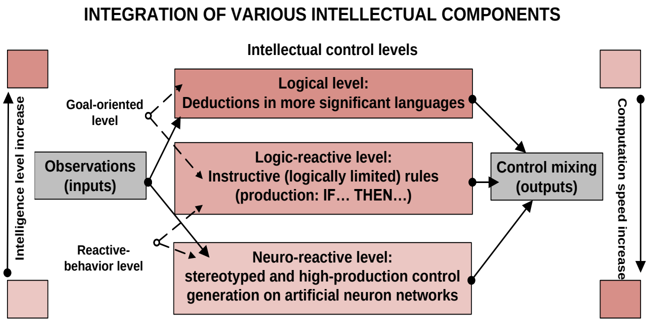

Fig.3. Intellectual control levels

Various artificial intelligence tools such as neuron networks, evolutionary, logical, etc., can be used for *mission planning problems*. Each of these classes features its own merits and drawbacks, especially against real-time requirements (Table 1).

Today, the tools are mainly selected heuristically. Maximum mitigation of drawbacks inherent to specific tools and the development of generic procedures of their combination for specific tasks is a global objective (Vassilyev et al., 2000). Choosing standard and management solutions optimal (or rational) in specific situations is a base for experience systematization at upper control levels.

Table 1. Artificial intelligence (AI) tools

AI Tools	Typical Merits	Typical Drawbacks
I. Neuron networks	1. Applicable in multi-factor problems with poor formalizability of patterns 2. High granularity of parallelism and speed 3. Learning ability	1. The need for learning information: a representative set of “input/output” examples (“rather eye than brain”). 2. Slow learning
II. Evolutionary (genetic)	1. High granularity of parallelism and speed	1. Application efficiency unknown a priori 2. Rather self-organization of elements than a constructive process.
III. Production	1. Capability of representing descriptive-constructive knowledge and reflection 2. Naturalness of rules (IF… THEN…).	1. Difficult to execute large production bases, insufficient structurization 2. Difficult to ensure correctness
IV. Object-oriented (semantic networks, frames, etc.)	1. Good structurization 2. High speed of property inheritance and other mechanisms	1. Complexity of programming (abandoning AI ideals) 2. Insufficient expressive power
V. Logical	1. High expressive power 2. Correctness 3. High complexity of off-line tasks	1. Insufficient speed, traditional applications are off-line 2. Traditionally poor compatibility with heuristics and experience 3. Unsolvability of rich logics 4. Insufficiency of a single logic
VI. Object-logical	1. Combine the merits of object-oriented and logical models	1. Drawback of logical models 2. Complexity of programming
VII. Multi-agent architectures	1. Allow for reflection and self-organization	1. Correctness and effectiveness of operation require to develop a relevant theory

As soon as the number of possible situations is huge, a priori generation and storage of all situations is impossible and hardly practical – one should point out the sets of “similar” situations and apply the same solutions to the situations from the same set. In control theory, such approach was named *unified control* (Novikov, 2013), and the related control solutions – *case-based reasoning*.

It is clear that a priori limitation of a class of possible controls, on the one hand, decreases the control effectiveness, and on the other hand enables the reduction of information load on the control subject and the opportunity for it to maximize both its own and other experience in a new situation.

The application of typical control decisions is the most effective in certain management tasks as well as in computerized training systems for process operators and engineers.

A class of automatic control systems based on DA+KBS (Data Analysis and Knowledge-Based Systems) technology, i.e., data analysis, knowledge revelation, representation, and processing, has been developing rapidly. Application efficiency of such systems in control tasks at all levels results from the ability to compensate for the lack of a priori information about the control object in case of poorly formalized input signals and system structure as well as when nonlinear models are required.

Generally, *knowledge management* is defined as a process of systematic and purposeful development, dissemination and application of knowledge (information) critical for enterprise's strategy and goals (Nonaka and Tackeuchi, 1995). Knowledge management comprises of 2 components: organizational and technological. The organizational part is a variety of managerial procedures, which allow the organization to store, structure, and analyze the information for its effective current and future application in production process control.

Knowledge management in process control systems enables the application of control techniques with intelligent predictive models (automatic control or managerial decision-making support) as well as of network, multi-agent, and multimodal techniques.

The operation of Knowledge-Based Manufacturing Systems (KBMS) can be represented as the interaction of basic elements (e.g., agents). The implementation of a specific interaction between elements at a current instant is determined by elements' response to environment change (Mizyun, 2011). The co-ordination of concurrent operation of elements in an integrated system is based on the development of flexible associative relations, which form a distributed associative environment of the informational interrelation.

The class of knowledge used today in production process control systems is more extensive than the expert knowledge class (Bakhtadze et al., 2012a). In KBMS, artificial intelligence operating with process knowledge along with expert knowledge are widely used. The term "process knowledge" means formalized process operation regularities obtained by means of DA.

In process of control system development and its adaptive tuning during real-time operation, procedural knowledge are iteratively transformed into declarative (non-procedural) ones, and vice versa. For such systems, application of fuzzy logic and fuzzy control algorithms, genetic algorithms, neuron networks and hybrid technologies is typical.

The a*ssociative search* method based on *virtual model* development (Bakhtadze et al., 2012b) exemplifies the DA+KBS technology. The associative search procedure builds a model of operator's prediction process for making a control decision based on knowledge and experience. In the model, operator's knowledge is replaced with the patterns retrieved form historical and on-line data using data mining techniques and associations. Instead of dynamic object's time approximation the associative search aims at building a new predictive model at each time step (a virtual model) using a set of historical data (associations) generated at the learning stage. Clustering, i.e., "learning without teacher" is an effective technique to generate associations. A control decision-maker may be a process operator, a supervisor or a plant manager dependent on the decision-making level.

The development of associative search algorithms can employ fuzzy logic techniques based on production-type models. However, the application of fuzzy techniques notwithstanding all their clear advantages significantly reduces the computing speed – the factor critically important for the efficiency of many industrial processes. This fact along with principal non-formalizability of a number of factors justifies the need for algorithms combining the advantages of the fuzzy approach and associative search algorithms.

It looks reasonable to employ wavelet analysis in identification tasks, in particular, for building predictive models using associative search techniques. Such approach may be relevant under non-stationary conditions either for non-stationary input signal or in case of unmodeled plant's dynamics.

4. NEW PRODUCTION CONTROL STRUCTURES

Multi-agent and network control structures are gaining increasing popularity as alternatives to traditional integrated systems. The effectiveness of production control on the basis of network interaction is caused on the one hand by the capability to execute various tasks (with different effectiveness) for different functional elements of production systems and on the other hand the ability of flexible adjustment of such structure to dynamic changes of operating conditions.

The examples are:

- project management tasks where the same set of contractors can implement various job packages, and the employees of functional departments may manage projects during their implementation;
- corporate management tasks where temporary role allocation among departments varies dependent on the order secured by the enterprise subject to complex supply chains and product customization to customer requirements.

A network structure is actually a set of initially equal agents where temporary hierarchical or other structures may arise dependent on the tasks executed by the system. The orderliness of interaction and the control mechanism (hierarchy) in a network structure result from the need in specialization enabling effective solution of partial problems.

Important results in the control of complex dynamic systems with network structures were obtained by Fradkov's school (Fradkov et al., 2009). In particular, adaptive controllers were synthesized, which do not use any information about network objects' parameters and are applicable under uncertainty conditions.

In recent years, the need for control systems implementing cross-system and/or interregional integration on the basis of multi-agent technology is emphasized (Dave et al., 2011). A number of specialists consider this approach as able to combine the capabilities of a global control system to reasoning and analysis of production situation and generating control decisions on that basis. The modeling of complex control systems based on multi-agent approach is called Agent-Based Modeling (ABM).

At an early stage of multi-agent control system development, a knowledge-based agent paradigm rested upon the traditional logical approach. However, such approach soon demonstrated its limitation due to a number of problems, such as:

- non-resolvability of the first-order predicate calculus underlying the approach
- the difficulty of inference search (hence, the heuristic search as the framework of AI problem solving methodology)
- problems incapable of algorithmic solutions; the need for decision-making in the situations where getting optimal or precise answers is impossible or too laborious
- pointing out significant qualitative characteristics of a situation, in which an agent is operating
- the need for accepting solutions based on inaccurate, insufficient or ill-conditioned information
- the need for using meta-level knowledge for more perfect decision-making control strategies
- the difficulty of logic-physical interface design,

etc. (Luger, 2004).

Furthermore, such agent's mental features as preferences, persuasions, wishes, intentions, commitments to other agents, etc., cannot be expressed in classical logic terms. New toolkits such as values logic, special variants of constructive, nonmonotonic, inductive and modal logics turned out to be more successful (Vassilyev et al., 2000, Finn, 2009, Anshakov and Gerdely, 2010) from realizability viewpoint. Here, the combination of deduction with production, analogy and abduction procedures synthetically developed in the JSM method is used.

New decision-making techniques under multicriteriality, uncertainty and risk conditions are increasingly used as well as the methods for teaching an agent another agent's preferences for communication with the latter one. Artificial neuron networks (ANN) and various pattern recognition techniques are combined with logical and other AI methods to facilitate the logic-physical interface and other applications.

Multi-agent system architectures implemented in modern control systems can be categorized as follows:

- Deliberative agent architectures, i.e., architectures based on AI concepts and techniques
- Reactive agent architectures, i.e., architectures based on the behavior and the response to external events, in particular, the ones using game theory, scenario-based virtual world models, etc.
- Hybrid agent architectures.

The present-day trend in both multi-agent system and game theories as well as in the AI (the two latter fields are aimed at higher levels of agent's architecture) shows a tendency to their integration. Here, the game theory (within the so-called *algorithmic game theory*) is evolving "top-down": from a generic game description to its decentralization and the investigation of the opportunity of autonomous realization of behavior mechanisms and equilibrium implementation (Nisan et al., 2009). On the contrary, the MAS theory is moving "bottom-up", i.e., in a parallel but, due to the localization of scientific communities, different way and strives more and more to allow for strategic behavior and develop standard test problems and scenarios (Shoham, 2008). The need for the latter ones is caused by the fact that in most cases specific heuristic algorithms (whose number is growing rapidly due to the popularity of multi-agent research area) are used at the tactical level; these algorithms need to be compared with each other per complexity, efficiency, etc. Therefore, the hierarchy of the agent's structure and the variety of tasks accomplished at each level require the usage of a hierarchy of different (heterogeneous) interrelated models (Novikov, 2012) as well as the interpenetration of methods, for example, the AI and the game-theoretical ones (Vassilyev et al., 2000b).

Network structures are implemented as "agency" without any permanent interrelations, while the links between them appear (e.g., as a linear or an array structure) for the time needed to accomplish the task faced by the system; then the links disappear until a new task arises, etc. (Novikov and Novikov, 2013). In other words, the variety of tasks engenders temporary hierarchies in a degenerate structure. Such approach on the one hand demonstrates utmost flexibility and efficiency under changing conditions. On the other hand a well-developed set of models and optimization techniques for hierarchical technical-organizational structures can be applied to solve structural synthesis problems.

The application of the *bounded rationality concept* is frequently observed: under the lack of time, opportunity or necessity, feasible pseudo-optimal controls ("anytime controls" (McCarthy, 2007)), are searched (often heuristically), justified by the common sense and applied instead of the optimal ones.

A switch is imminent from the so-called "c-cube" paradigm, where control, computing, and communication problems are solved simultaneously, to the "c in the fifth" concept, which presumes the above mentioned problems to be solved subject to cost (in a broad sense) considerations over the whole of the system's lifecycle including the concurrent design of both the control system and the plant (Novikov, 2013).

Finally, for heterogeneous, hierarchical intellectual control models, the following generic problem classes can be identified. First, intrinsic difficulties relevant to the employed mathematical tools arise for each level models. Second, the set of "seamed" models inherits all negative properties of each component. For example, if at least one model in a chain does not enable analytical treatment, then the whole chain is doomed to simulation only. The computation speed will align with the worst result over all levels. The need arises for estimating the comparative efficiency of solving aggregated problems, etc. As a whole, one can foresee the shift of the focus in control theory and practice from hierarchies and networks to heterogeneous network hierarchies and hierarchy networks of production control systems. The control is getting situational (contextual (Popper, 1992)), and a broader understanding of rationality is being used (Bernays, 1974).

5. CONCLUSIONS

Control system integration at different levels of production process should rest on a novel methodology allowing for new types of manufacturing organization and the advanced development of information technologies as against the automation and technical re-equipment of industrial plants. Intellectual control based on state-of-the-art knowledge management techniques provides such methodology. Application of AI, network, multimodal, group, and multi-agent production control techniques looks the most promising.

The development of new generation integrated flexible intelligent control systems employing the wide range of AI-based knowledge, simulation, optimization, and game-theoretical models and methods poses a challenge to the modern control theory and applications.

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