Methods of artificial intelligence for cyber-physical systems

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***Abstract**: Cyber-physical systems (CPS) are the core of the Fourth industrial revolution and the Industry 4.0 initiative. They are facing many challenges, addressing them requires attracting and using new methods and techniques from the field of artificial intelligence and big data to make intelligent decisions and perform effective data analysis. The paper presents an analyze of the current trends and challenges in the development of cyber-physical systems and the ever-increasing interest in the methods and approaches of artificial intelligence and its application in the life cycle phases of design, analysis, implementation and maintenance of CPS. There are two aspects that are the focus of attention and analysis: (1) the computing by intelligence and (2) the computing for intelligence. Finally some ideas for using different methods and approaches of artificial intelligence for achieving interoperability and autonomy of CPS are proposed.*

***Keywords**:* CYBER-PHYSICAL SYSTEM, INDUSTRY 4.0, ARTIFICIAL INTELLIGENCE, METHODS, ONTOLOGY, AGENTS

1. Introduction

The evolution of personal computers into smart devices and their miniaturization, as well as the unstoppable development of the Internet and technologies related to it, led to the strengthening of the tendency to provide IT services and infrastructure through intelligent networks (computing clouds) and the construction of a world surrounded by ubiquitous computer calculations. The development of embedded systems and the achievement of their autonomy, as well as their wireless connection with each other and with the Internet, brought the physical world closer to the virtual in the form of so-called cyber-physical systems. The new Internet protocol IPv62, introduced in 2012, made possible the creation of the Internet of Things and services.

The initiative "Industry 4.0" has a huge potential, which allows creating wider opportunities to satisfy individual customer requirements, achieving greater flexibility of manufacturing and enterprise systems, enhancing the potential for optimal decision-making and increasing productivity and efficiency of the resources used or planned, as well as arising the prerequisites for creating value through new services. The concepts of Industry 4.0 initiative and that of digital transformation have also been transferred to a number of non-industrial and public sectors, contributing to increasing their efficiency and sustainability. The Industry 4.0 Working Group [1] argues that at the core of the fourth industrial revolution and the Industry 4.0 initiative are cyber-physical systems. In [2], eight technology clusters with the greatest contribution and importance to the development of Industry 4.0 are defined. The cluster on Industrial Internet of Things (IIoT) that includes the IIoT-related technologies and Cyber-Physical Systems (CPS) is the largest cluster, forming the core of Industry 4.0.

Cyber-physical systems (CPS) are physical and engineering systems whose operation is monitored, coordinated, controlled and integrated by a computing and communication core [3]. They are unique in that components can be distributed both spatially and temporally, and include complex networks of controllers with real-time feedback and communication. The structural and behavioural complexity of cyber-physical systems poses major challenges to the methods and environments for their design and analysis. It is necessary to develop the theoretical foundations of CPS, as well as to create software platforms with appropriately defined levels of abstraction, architecture, languages for modelling different aspects of CPS and transformations between these models. All this requires the development and application of modern methods and technologies aimed at integrated access to distributed information and data from sources that grow in number, type and complexity every day. Data from distributed information sources are in different formats, which makes it technically difficult to access and use the information offered in terms of interoperability between different hardware and software technologies.

Addressing many important challenges to CPS require attracting and using new methods and techniques from the field of artificial intelligence and big data to make intelligent decisions and perform effective data analysis based on large amount of data and efficient and intensive computations, as well as integration with other powerful computing systems, including cloud and fog applications. All these technical challenges in the design and analysis of CPS arise from the need to build a bridge between the sequential semantics and the parallel physical world and connect them to the solution of different types of engineering tasks.

The main purpose of the paper is to analyze the current trends in the development of cyber-physical systems as the core of the Industry 4.0 initiative and the ever-increasing interest in the methods and approaches of artificial intelligence and its application in the life cycle phases of design, analysis, implementation and maintenance of CPS.There are two aspects that are the focus of attention: (1) the computing by intelligence and (2) the computing for intelligence, as they are defined in [4].

The paper is presented in four parts. After the Introduction, the second part of the paper presents the basic characteristics and challenges to the CPS. The third part is dedicated to a modern look at artificial intelligence methods and their importance for solving various tasks in the field of cyber-physical systems and the Industry 4.0 initiative. Special attention in the fourth part is given to some of the most attractive methods of artificial intelligence in solving interoperability problems and the approach to creating autonomous systems using intelligent agents and multi-agent systems. Finally, some conclusions reflecting the results of the analysis are presented.

2. Basic characteristics and challenges to the CPS

2.1. Basic architecture and characteristics of CPS

The impact of CPS is revolutionary and pervasive, as argued by the CPS Public Working Group at NIST [5], as the development of these systems is associated with the emergence of autonomous vehicles, smart grids, smart cities and homes, robots, smart medical devices, telemedicine, Internet of Things (IoT) and more. Some of the main non-functional properties distinguishing CPS are: real-time, configurability, scalability, context awareness, interoperability, resilience and security. Synergies between cyber and physical systems can be at both the Nano level and the "system of systems" level. However science is still indebted to CPS, the lack of theoretical basis and methodologies creates barriers that can hinder the adoption, commercialization and market success of new applications of CPS [6]. The basic architecture of CPS is shown in Fig.1, including the both parts Cyber and Physical, connected through sensors, actuators and Network. The basic operations of Cyber part are computing, communication and control,

In [7], a very detailed analysis of the CPS characteristics is presented. The authors define 19 most cited lower-order characteristics of CPS, which are aggregated in the following eight clusters:

Cluster 1: Complexity/heterogeneity/encapsulation;
Cluster 2: Interoperability, connectivity, communication, networking capability
Cluster 3: Service orientation,
Cluster 4: Modularity, autonomy, self-capabilities, decentralization;
Cluster 5: Virtualization, real-time capability;
Cluster 6: Computational capability;
Cluster 7: Cooperation, collaboration;
Cluster 8: Dynamic reconfigurability, adaptability.

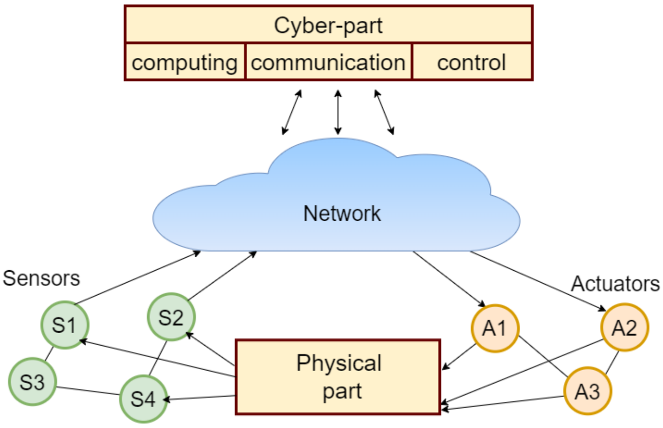

***Fig.1:** Basic architecture of CPS*

2.2. Basic challenges to the CPS

The technical challenges to CPS are discussed in [8] and summarized in Fig.2. Cyber-physical systems include a large number of sensors, actuators and computing devices that exchange diverse data presented in different formats and temporal sequences. This requires new approaches providing the opportunity to work with a dynamically changing network topology of the system (1). The distributed nature of the physical system structure, computation, and communications creates major challenges in operational performance and ensuring safe system operation, security, and resilience in the face of environmental impact, component and system failures, and unregulated actions and cyber-attacks (2). Especially important challenge is the development of methods that integrate the discrete dynamics of the computing part with the continuous dynamics of the physical part and the stochastic nature of communications, which must be expanded to cover a wider context. The emphasis on these approaches is on the communication between the different components of the system. Methods are needed that combine systems with continuous dynamics with those of a discrete-event nature. Different time scales and dimensionality must also be taken into account (3). The emphasis on the approaches connected to the challenge (4) - networked control is on the communication between the different components of the system. There are two main approaches for data acquisition from the physical part of the CPS: timed driven and event driven sampling. The latter approach requires continuous monitoring of the physical system. There is a compromise approach, the so-called self-triggering approach that is related to the determination of safe intervals during which the physical system is not observed and the time when the data is collected. The main obstacles in the development of networked control for CPS are the event- and time-driven computing, the transmission failures, the varying time-delays, and also system reconfigurations. Particular attention is also paid to methods of addressing the effect of delayed network signals, such as scheduling or stability analysis methods. The next important challenge is sensor and sensor-actuator networks and their inclusion in the design process (5). The reliability, safety and security of the CPS largely depend on the quality and accuracy of the software components, which must undergo verification, validation and testing throughout the design stages (6). This requires both the development of new verification and validation methods and the use of new software models (software development life cycle models). The joint design of control and planning systems (7) is a widely researched multidisciplinary task whose successful solution in CPS is complicated by the networked nature of CPS, network time delays, and system-wide robustness issues. Programming abstractions should be used at different levels covering different aspects of the designed system (8). Meta-level CPS architectures must be complete. The development of the new paradigm should follow the principle: "Globally - virtual, locally - physical" (9).

1	Dynamic chenging topology
2	Robustness, safety, security
3	Hybrid system modeling and control
4	Networked control
5	Sensor, actuator networks
6	Verification and validation
7	Control and scheduling co-design
8	Computational abstraction
9	Archtecture

***Fig.2:** Basic challenges to the CPS*

3. Short analysis of the methods of Artificial Intelligence

3.1. Computing by intelligence

Artificial intelligence is being used more and more and has an increasingly tangible impact in different areas of industry and society. The successful solution of many different tasks and problems related to the achievement of the goals of the Industry 4.0 initiative and guaranteeing high added value is thanks to the application of the latest methods and achievements in the field of artificial intelligence. More and more often, the enterprises and factories of the future are associated with the development of artificial intelligence and are mentioned with terms such as: smart factory, smart grids, cognitive enterprises or intelligent manufacturing. What all these paradigms have in common is that they are all based on a new principle of integration of the physical and cyber parts, through a comprehensive and complete design, development and evolution of the knowledge of the cyber-physical system of systems and the integration of artificial intelligence into the various technologies used.

Biologically embodied intelligence is presented in the machine through the generic intelligence that is composed of Data Intelligence, Perceptual Intelligence, Cognitive Intelligence and Autonomous Intelligence [4]. All these intelligent abilities are part of computing by Intelligence as shown in Fig.3. Data intelligence includes the computer's ability to formalize, express, calculate, remember, and store data rapidly. The most important and popular Data Intelligence methods are Artificial Neural Networks (ANN), evolutionary computing and fuzzy systems. Computational models have a high degree of complexity and can refer to various areas: digital, analog, hybrid, discrete-event, graphs, etc. Great successes have been achieved in the field of neural networks, such as the emergence of so-called convolutional neural networks (CNN) and reinforcement neural network (RNN), which open the way to processing big data and improving the accuracy of classification, identification and prediction tasks. Development in the field of neural networks is also a catalyst for success in the field of machine learning, where deep learning and deep reinforcement learning are successfully developed. Gaining popularity and wide scientific interest in the 1980s, Lotfi Zadeh fuzzy systems are particularly applicable in areas where sufficient data is lacking, such as: signal and image processing, control, identification, and decision making. The third group of methods, including evolutionary calculations and programming, as well as genetic methods and algorithms, are primarily related to solving optimization tasks.

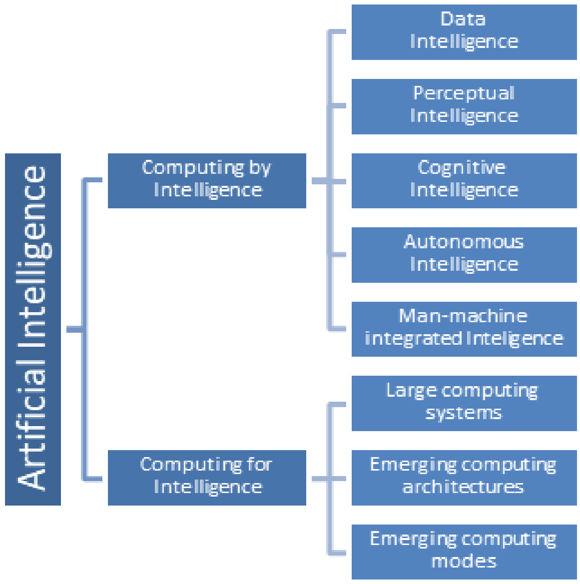

Fig.3: *Classifications of methods in Artificial Intelligence [4]*

Perceptual intelligence refers to receiving information such as voice, images and video through various sensors and I/O devices. It can also include multi-modal perception, signal extraction, selection and processing, data fusion based on different sensors for vision, hearing, smelling, tasting. The use of recognition and machine learning methods has led to significant advances in voice and image recognition. Another important direction is the development and use of intelligent sensors, of particular value being sensors with the ability to be self-aware and respond to remedy situations.

Cognitive intelligence refers to a machine's ability to understand and reason, think and explain. It requires understanding the relationship between data and analyzing the logic of structured data. The main directions in which cognitive intelligence is developing are natural language processing (machine translators, text generators, etc.), causal inference (a conceptual network of causal events for extracting causal relationships from text) and reasoning on knowledge (knowledge acquisition, representation, storage, modeling, integration, understanding, and management). Knowledge reasoning may be based on knowledge graphs, logical rules, graph-structure, or neural-network-based reasoning.

Autonomous intelligence refers to the ability of a machine to acquire a self-governing ego and consciousness. It develops in three directions: transfer learning, meta-learning and autonomous learning. Transfer learning is based on accumulating experience from past data, and for this purpose, machine learning methods are applied. Meta-Learning supports machine learning based on the use of meta-knowledge, finding application in the absence of sufficient training data and in self-learning conditions. Successfully copes in the cases of similar, homogeneous tasks, transferring the learned. Autonomous learning also includes models of the external open world. From the indicated methods, it can be seen that quite often combinations of different types of intelligence are used, especially in cases of solving more complex tasks.

Despite advances in machine intelligence, many complex scenarios and tasks require the use of human intelligence and other computational methods such as statistical ones. The possibilities for this are through human-computer interaction, human-machine integration, and brain computer interface.

3.2. Computing for intelligence

Although the major advances in development of machine intelligence algorithms and tools, the computing power remains a bottleneck for intelligent computing. An opportunity to deal with this problem is the introduction of distributed structures and calculations, such as: federated learning, Large Computing Systems as High-Performance Computing or Edge, Fog, and Cloud Computing. The use of emerging computing architectures as accelerators and in-memory computing results in efficient power consumption, cheaper hardware, and an easier debugging process. Another possibility to deal with the complexity of calculations is the introduction of new Emerging Computing Modes as Quantum Computing, Neuromorphic Computing, Photonic Computing and Biocomputing. The characteristic of all these innovative solutions is that they use the algorithms and methods of artificial intelligence to varying degrees.

4. SOME IDEAS OF USING ARTIFICIAL INTELLIGENCE FOR CPS

4.1. Ontological approach for interoperability

Achieving interoperability through the use of semantic technologies can be represented as a sequence of three main processes: converting data from heterogeneous sources (relational databases, XML, tables, documents), processing integrated models (unification, editing and logical analysis) and information extraction (conversion, visualization). During the three stages, different methods are used to control the data being integrated, to sort the data, to reject duplicates, to extract information, to perform logical analysis and verification.

The integration can be done in different ways, going through different stages, using different languages, technologies and mechanisms. Ontology-based integration covers processes similar to ETL transformations: (E) xtracte from a data source, (T) transform into an RDF model (target ontology), and (L) oad e into ontological data stores. The main difference is that in the ontology-based integration, both structured and unstructured data can be used, and the semantics in the ontology can be set in the transformation process, or subsequently in the processing of the ontology model through the operations on ontologies: merging, mapping, alignment, integration. The reference ontology can be used as the target ontology. The transformation is repeated, when the data changes. Fig.4 illustrates an ontology integration method representing the integration of results obtained in the technology space (TP) of "BNF", which by means of "Scheme 1" and "Scheme 2" are stored in the TP of "RDB" as a database, which in turn have dynamic correspondences with "Local Ontology 1" and "Local Ontology 2", respectively. These two ontologies can be mapped to each other based on the existing reference ontology.

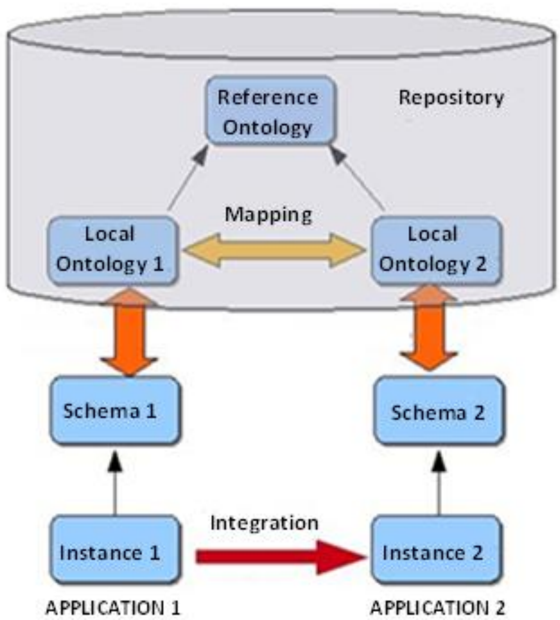

Fig.4: *An example of ontological integration*

4.2. Multi-agent systems

CPS development is much more than the union of computational and physical systems, and to apply CPS principles to new applications, new methods and tools are needed. CPSs integrate computational, network, and physical dynamics, featuring a high degree of heterogeneity and parallelism. As a result, software design techniques are insufficient. New approaches, methods, algorithms, and techniques are needed to support the CPS analysis and design process using execution platforms based on different software architectures.

In [9], three types of software architecture categories are defined and analyzed: component-based, service-oriented, and agent-based. The analysis shows that the agent-based approach has greater advantages in ensuring the autonomy of CPS objects, while the service-oriented approach is more suitable for achieving their interoperability. The advantages of agent-based architecture in terms of non-functional properties, especially in terms of configurability and reliability, make this approach highly suitable for the field of CPS. Other non-functional properties such as scalability, security and context awareness can be improved using the combination with knowledge-based approaches.

The concepts of CPS are closely related to agent-based systems, due to their main properties such as: autonomy, sociality, reactivity, proactivity and mobility. Different approaches and methods are used to ensure the useful characteristics of agents in different application areas, such as modeling, monitoring, control, diagnostics, etc. An important conclusion to be drawn from the analysis of the approach is that the results are more successful when the agent-based approach is combined with other approaches, methods and tools, such as model-driven development.

To achieve these features, the agent functions are divided into 4 sub-functions: Monitoring, Analysis, Planning and Execution (MAPE), which share knowledge, as shown in Fig.5. They underlie the architectural aspects of autonomous systems and obey an intelligent control loop known as MAPE-K (K is for Knowledge) [10]. This cycle is similar to and inspired by the general agent model proposed by Russell and Norvig [11], where an intelligent agent perceives its environment through sensors and uses these perceptions to define actions (effectors) to be performed on the environment.

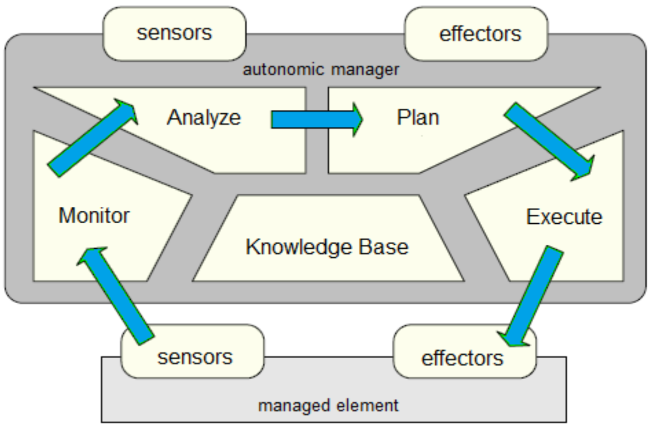

Fig.5: *MAPE-K control loop, according [10]*

5. CONCLUSIONS

Based on the CPS analysis and the presented classification of artificial intelligence methods in the two aspects (1) calculations with intelligence and (2) calculations for intelligence, the following main conclusions can be drawn:

- The stormy invasion of artificial intelligence methods in the field of CPS and IIoT requires changes in the 5-layer reference architecture of CPS, due to the inclusion of intelligent and cognitive methods in all layers of the architecture;
- As the requirements for CPS increase in terms of security, safety, reliability and resilience, changes are required in the life cycle models of these systems, including the introduction of risk assessment where possible.
- Advances in the field of artificial intelligence and especially in the field of Data Intelligence and in particular the high degree of applicability of convolutional neural networks and related deep learning opens the doors to address the challenges of CPS, such as those related to their modeling, diagnostics and maintenance, or regarding their cyber security.
- The idea of achieving interoperability enables the achievement of vertical and horizontal integration, based on different actions between local ontologies and the use of a reference one.
- The idea of using multi-agent systems as an approach to achieving autonomy and self-organization of the CPS allows the use of intelligent adaptive and predictive technical systems with self-X functions and cognitive information processing in continuous interaction with the environment, the Industry 4.0 initiative implies the integration of cyber-physical systems (CPS), the Internet of Things (IoT) and cloud computing, leading to what is called the "smart factory".

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