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MACHINE LEARNING IN CYBER-PHYSICAL SYSTEMS AND *MANUFACTURING SINGULARITY* – IT DOES NOT MEAN TOTAL AUTOMATION, HUMAN IS STILL IN THE CENTRE:

PART II – I^n-CPS AND A VIEW FROM COMMUNITY ON INDUSTRY 4.0 IMPACT ON SOCIETY

In many discourses, popular as well as scientific, it is suggested that the "massive" use of Artificial Intelligence (AI), including Machine Learning (ML), and reaching the point of "singularity" through so-called Artificial General Intelligence (AGI), and Artificial Super-Intelligence (ASI), will completely exclude humans from decision making, resulting in total dominance of machines over human race. Speaking in terms of manufacturing systems, it would mean that the intelligence and *total* automation would be achieved (once the humans are excluded). The hypothesis presented in this paper is that there is a limit of AI/ML autonomy capacity, and more concretely, the ML algorithms will be not able to become totally autonomous and, consequently, the human role will be indispensable. In the context of the question, the authors of this paper introduce the notion of the *manufacturing singularity* and present an *intelligent machine architecture* towards the manufacturing singularity, arguing that the intelligent machine will always be human dependent. In addition, concerning the manufacturing, the human will remain in the centre of Cyber-Physical Systems (CPS) and in Industry 4.0. The methodology to support this argument is inductive, similarly to the methodology applied in a number of texts found in literature, and based on computational requirements of inductive inference based machine learning. The argumentation is supported by several experiments that demonstrate the role of human within the process of machine learning. Based on the exposed considerations, a generic architecture of intelligent CPS, with embedded ML functional modules in multiple learning loops, is proposed in order to evaluate way of use of ML functionality in the context of CPS. Similar to other papers found in literature, due to the (informal) inductive methodology applied, considering that this methodology does not provide an absolute proof in favour of, or against, the hypothesis defined, the paper represents a kind of position paper. The paper is divided into two parts. In the first part a review of argumentation from literature in favour of and against the thesis on the human role in future was presented, as well as the concept of the *manufacturing singularity* was introduced. Furthermore, an *intelligent machine architecture* towards the manufacturing singularity was proposed, arguing that the intelligent machine will be always human dependent

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and, concerning the manufacturing, the human will remain in the centre. The argumentation is based on the phenomenon related to computational machine learning paradigm, as intrinsic feature of the AI/ML[1], through the inductive inference based ML algorithms, whose effectiveness is conditioned by the human participation. In the second part, an architecture of the Cyber-Physical (Production) Systems (CPPS) with multiple learning loops is presented, together with a set of experiments demonstrating the indispensable human role. Finally, a discussion of the problem from the manufacturing community point of view on future of human role in Industry 4.0 as the environment for advanced AI/ML applications is registered.

1. INTRODUCTION[2]

One of the main requirements for designing and operating new manufacturing devices and systems within the concept of Industry 4.0 (I4.0) is to embed Artificial Intelligence (AI) and Machine Learning (ML) functionalities in virtually any single component, making in fact, I4.0 based systems composed almost exclusively from so called, “smart objects”[3]. Such requirement of using "massively" AI/ML naturally raises a number of questions, where one of the most important questions is “where are the limits”?

It is possible to define different types of limits, depending on the context in which the considerations are made, but phenomenologically, the most important question, from which all others stem, is “whether there is a limit of AI/ML in comparison with the human intelligence”. The non-existence of such limit means that the machines could become autonomous, and in the limit, *totally* autonomous, up to the exclusion of humans from any single issue’s decision making. That scenario could mean the extinction of human race, as warned by some prominent personalities [1–3].

However, there is no positive response to this truly big question. Considering literature, there could be found opposite positions, all of them based on inductive argumentation[4]. As the inductive methodology, by some philosophy of science models, doesn’t guarantee positive conclusions, all conclusions, based on induction, virtually could be considered only as positions or as guidance to orient further research and applications [4]. This fact could actually explain the co-existence of opposite positions when comparing AI/ML capacity with human capacity. From manufacturing engineering point of view, the question has relevance in the context of designing and operation of future manufacturing devices (machines) and systems, especially within the context of newly promoted I4.0. Concerning the I4.0, and in particular Cyber-Physical Production Systems (CPPS, or, further, CPS[5]) as one of the most important I4.0 constructs (also, models or instruments), the question is if the AI/ML systems

[1] Since AI and ML are both conceptually distinct and practically intersecting fields at the same time, the terms cannot be used interchangeably. Hence, in this paper we have used the term AI/ML to refer to these two fields combined.

[2] The paper is based on the Keynote Lecture presented on the 31st CIRP Sponsored Conference on *Supervising and Diagnostics of Machining Systems*, 08-12 March 2020, Karpacz, Poland.

[3] It should not be understood that the use and embedding of AI/ML in industrial devices is the only determinant of I4.0. There are other features that, together with AI/ML, as well as the way of their relationship, determine I4.0, and make I4.0, but these will be not consider in this paper as their consideration doesn’t affect the main hypothesis of this paper.

[4] Although inductive reasoning, i.e. ‘inductive inference’, is one of the ´classical’ inference methodologies, and a regular scientific methodology, its value is questioned by some philosophy of science models, e.g. by Popper´s model,

[5] For manufacturing industry, virtually more appropriate term would be Cyber-Physical Production Systems (CPPS). However, for short, we will use the term CPS as more general, without loosing any CPS particular feature concerning manufacturing.

could learn, and subsequently generate and operate the (intelligent) control programs, without human role within the process, i.e. without human intervention. If the answer is 'yes', it would mean a strong suggestion of possible autonomy for more and the most complex tasks, like, for instance, autonomous decisions on production at all. This scenario would totally exclude human from the production, and ultimately from running economy. This scenario would be just a part, in the domain of production, of the most extreme vision of the AI/ML capacity, which would result in extinction of human race (see below in the second chapter).

The hypothesis presented in this paper is based on the existence of a limit of AI/ML autonomy capacity. More concretely, the ML algorithms will be not able to become fully autonomous, being the human role indispensable. In the context of this hypothesis, the authors introduce the notion of the *manufacturing singularity* and propose an *intelligent machine architecture* towards supporting it. They argue that the intelligent machine will be human dependent, and human will remain in the centre of CPPS/CPS, including in I4.0. The methodology to support this claim is inductive (based on informal induction methodology), similarly to the methodology applied in a number of texts found in literature. Therefore, considering the limitations of that methodology, the paper is kind of a position paper, where the human will be inevitably in the centre of the technological development, including AI/ML based development.

The paper is divided into two parts. In the first part, a review of argumentation from literature in favour of and against the thesis on the human role in future is presented. A concept of the *manufacturing singularity* is introduced, as well as an *intelligent machine architecture* to support it, is presented. The argumentation is based on the phenomenon related to computational machine learning paradigm, as intrinsic feature of the AI/ML, through the inductive inference based machine learning algorithms. In the second part, an architecture of CPPS with multiple learning loops is presented, together with a set of experiments demonstrating the indispensable human role. Finally, a discussion of the problem, from the manufacturing community point of view on future of human role in Industry 4.0 as the environment for advanced AI/ML applications, is documented.

Considering the previous considerations presented in the first part of this paper (PART I), this second part – Part II – is structured in Chapter 2 that presents a generic architecture of intelligent CPPS/CPS, with embedded ML functional modules and multiple learning loops, denominated as I^n-CPS. Follows the Chapter 3 that presents the results of four experiments that demonstrate the role of human within the process of machine learning. In the context of argumentation in favour of this paper's hypothesis, the Chapter 3 presents some quantitative results of the volume of the human intervention during the learning process, reinforcing the argumentation in favour that the human role will be indispensable. In the Chapter 4, a discussion of the problem from the manufacturing community point of view on future of human role in Industry 4.0 as the environment for advanced AI/ML applications, including the industry 4.0 impact on society, is given. Finally the Conclusions of this first part – Part II – are given.

2. AGI/ASI IN MANUFACTURING AND INDUSTRY

Artificial Narrow Intelligence (ANI), also known as "Weak" AI, Artificial General Intelligence (AGI), also known as "Strong" AI, and Artificial Super Intelligence (ASI) are common concepts in nowadays' spectrum of Artificial Intelligence definitions [5]. Simplifying, i) ANI is the AI programmed to execute a particular task and not driven by human context-aware interpretations, i.e., it cannot improve its processing capacity. It happens in the existing "intelligent" platforms (Siri, Azure Cognitive, Google Assistant, IBM's Watson, others) [6]; ii) AGI is seen as the system or device that can perform human like intelligent tasks. Machines are definitely faster than us humans on processing judgements, decisions, etc. However, the non-tangible abstraction and creativity the humans have, based, for instance, on their experience or consciousness are not easy to be created by machines. When the machine can handle this, then we have AGI [7]; and iii) ASI or super Intelligence, as the AI that surpass any human capacity, in the human's advantage - the one that, predictably, will make the human race dispensable [8]. Foremost visionary perspectives for this technological singularity announce, however, that human coexisting with intelligent machines or services, will have their capacities improved. Paraphrasing Ray Kurzweill at the Council on Foreign Relations (CFR) of 2017, "*AI will not displace humans, it's going to enhance us*".

While the number of publications of the actual paradigm of AI, i.e. ANI, in manufacturing and industry is metaphorically 'innumerable,' the number of publications on AGI in manufacturing and industry ASI is almost inexistent.

Just a few publications directly refer AGI/ASI applications to manufacturing. For example, in [9] as the title says, "*A reference framework and overall planning of industrial artificial intelligence (I-AI) for new application scenarios*", coining the term I-AGI: "Industrial AGI". Curiously, this is the only publication we found referring ASI manufacturing and industrial applications, i.e. I-ASI (Industrial ASI). In these terms, these publications are close to our concept, and to the term we have introduced, *manufacturing singularity*. In [10] the authors refer the role of AGI and its model they call *General Collective Intelligence* for the objective to achieve the *pervasive manufacturing*[6]. AGI is also referred in [12], in the context of the CPS for "*new generation Intelligent Manufacturing*" based on "Human-Cyber-Physical Systems" implying the role of humans in the future AGI/ASI based manufacturing as we are defending in this paper. [13], discusses some perspectives on AI/ML, that includes AGI as well on non-manufacturing area of engineering, i.e. "on Materials, Processes and Structures Engineering". In [14], which is an MSc thesis, AGI is also referred in the context of AI's role in "competitive advantage during industry 4.0", and, importantly, for manufacturing SMEs (the case study from South African SMEs).

AGI is also referred for the future in Design Engineering. While in [15], which is in the form of presentation slides, we find more elaboration on the role of AGI, in [16] AGI is only mentioned as an important instrument for future designs.

However, some papers, although show the awareness of AGI, do not elaborate any vision or perspective on AGI. e.g., in [17], AGI is referred only in the References. Also, in

[6] The term "Pervasive manufacturing" has its synonym "ubiquitous manufacturing" although some specific features could be discussed to make the difference. Anyway, the "ubiquitous manufacturing systems" (UMS) besides the use of "ubiquitous computational technology" is also interpreted as a large complex network, ubiquitously presented, see e.g. [11] (large hyper-complex manufacturing networks such as ubiquitous manufacturing system (UMS) … that might consist of millions of nodes, with inherent manifestations of dynamics, nonlinearity, uncertainty and 'chaos'." Nevertheless, AGI would have the fundamental role in the future developments of "pervasive" or "ubiquitous" manufacturing.

[18] an analysis of the investment trends in AI in different sectors, including manufacturing, is presented, but just mentioning AGI in the context of new approaches to AI, without any further related analysis or perspectives.

There are more, but not too many, publications from general area of AGI/ASI, that refer manufacturing as an of possible application domains among many others, but without value added in the context of the manufacturing science and practice. These were not considered for referencing.

References to neither *singularity* (related to manufacturing) nor *manufacturing singularity* were found.

The next two papers are interesting to refer. In accordance with the view of many that AGI/ASI is 'far' in the future, [19], although not originated from the manufacturing community, refers very far future manufacturing application area, related to "Interstellar Travel" supported by AGI. The authors have vision of manufacturing "*on-board*" or on "*planetary surface*", with capabilities "*building artefacts in the Space…manufacturing predefined spare parts capable of using local resources to a limited extent…for creating mechanisms, instrument components, and tools for having the flexibility to react to unexpected situations*".

Second, in already referred [20], one odd consequence of AGI/ASI application related to manufacturing is referred, which may be found in general literature of the domain. This is the hypothesis that AGI/ASI "turn out to be unfriendly toward humankind" and become (by Yudkowsky) a *paperclip maximiser*, that is, "*literally, a machine with the goal of maximizing the number of paper clips in the universe. Metaphorically, this would be an AI with the monotonous and ultimately unintentionally (on the part of its human designers) destructive goal of turning all the atoms in its path, including us, into something of no real use or value*".

Nevertheless, although this is an un-intelligent manifestation of the "general" and "super" intelligence, it just shows how strange could be that "super-intelligence". In fact, if it happens without human, it will have no sense and, in fact, practically incapable of any evolution – considering that the evolution is driven by some teleology. This would be another argument against exclusion of humans (however, in the context of optimistic thinking, it may be that the *paperclip maximiser* has some deeper meaning and purpose that we cannot understand on our actual (human) level of intelligence).

3. GENERIC ARCHITECTURE OF I^n-CPS – TOWARDS AN INTELLIGENT MACHINE ARCHITECTURE FOR *MANUFACTURING SINGULARITY*

3.1. GENERIC ARCHITECTURE OF INTELLIGENT CYBER-PHYSICAL SYSTEM WITH *n*-LOOP LEARNING (I^n-CPS)

From a practical point of view, the question is how to implement the above concepts, especially considering the demand for Industry 4.0, where CPS will be the main constructs of manufacturing systems.

The CPS concept is conceived as a new generation or a new paradigm for future control systems. It evolved from the classical control architecture characterized by feedbacks, i.e.

cybernetics based (Fig. 1) [21], to the more advanced architecture called CPS. This ‘more advanced architecture’, when abstracting the hardware/software implementation technology aspects, structurally is the same, since it is also based on feedback loops.

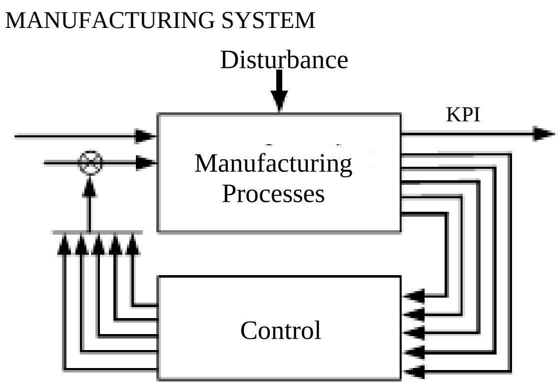

Fig. 1. “Classical”, or “conventional”, logical control architecture of Production or Manufacturing System (PS/MS)

Then, where is the difference?

Obviously, some of the qualitative differences are the new Information and Communication Technologies (ICT), externalisation of many feedback loops (while in the ‘classical’ model these are mainly internally located), so called ‘connectedness’, obviously ‘big data’, and virtually the most important for CPS from where the denomination came, computation and physical processes integration, i.e. cyber and physical.

There is the issue of AI/ML. Does AI/ML make the difference? Yes and no. No in the context that AI/ML was also considered and applied in ‘classical’ systems; and ‘Yes’ in the context of, again, new ICT, etc. (already referred above and in the Part I of this paper series).

Our questions are, i) “is the CPS architecture possible in the context of *manufacturing singularity*,” and ii) “does that architecture contribute on possible exclusion of humans from decision making,” as discussed in the previous chapters.

Recalling the fundamentals of the *intelligent machine architecture,* presented in the Chapter 4 of Part I [22], CPS could be considered as a constructor towards development of the *intelligent machine*, towards *manufacturing singularity,* following the architecture presented there, that includes *n*-loop learning.

Reviewing already extensive literature on CPS, e.g. the review in [23], the conclusion is that the majority of CPS definitions, and subsequent architectures, present fixed connections, or at most requiring changing only of the “physical” part of the CPS. Also, the majority do not consider embodiment of learning as one of the fundamental and critical modules, or at most consider the single-loop learning, as it (the single-loop learning) is defined in Chapter 4.

However, only one of the definitions found refers to an architecture that considers a double-loop feedback. Although the authors of that definition didn’t relate them, it possibly could imply the double-loop learning architecture of the intelligent machine. The referred definition is:

"Cyber-physical systems (CPS) are integrations of computation and physical processes. Embedded computers and networks monitor and control the physical processes, usually with feedback loops *where physical processes affect computations and vice versa*" [24] [italic by the authors of this paper].

Considering our *intelligent machine architecture*, as well as the definition by [24], it is possible to conceive the *n*-loop learning based architecture of CPS, as a candidate architecture towards building an intelligent machine in the context of *manufacturing singularity*.

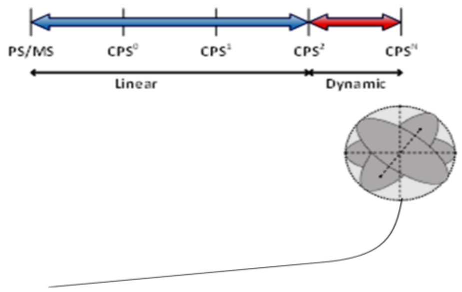

Fig. 2. CPS definitions and models spectrum, integrating both, linear and dynamic parts of the CPS models spectrum domain. [23]

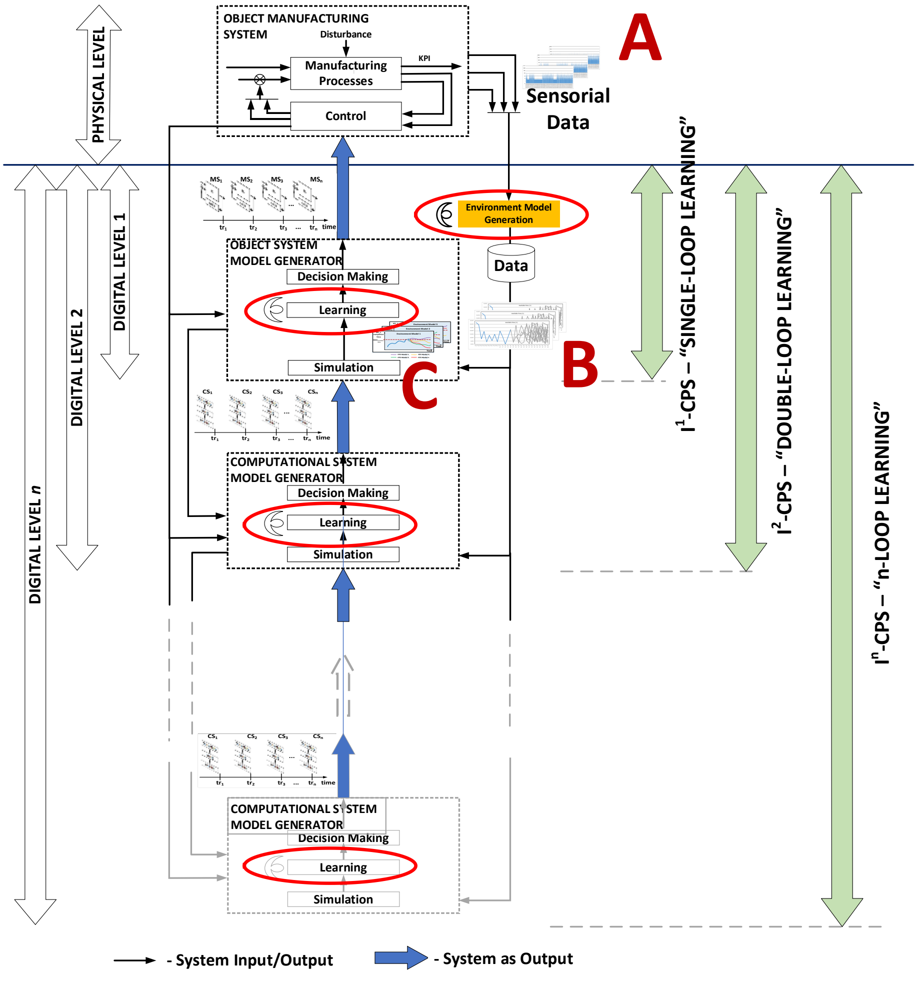

Fig. 3. Logical Architecture to model a *n*-loop learning CPS – I^n-CPS (adapted from [13])

In accordance with the notation in Chapter 4 – Part I [22], we could now denominate the CPS with embedded learning loops as I-CPS, where 'I' stands for 'Intelligent'. Consequently, adding the indicator for the levels of learning loops, we could have the following notations for different levels of 'intelligence' embedded in the CPS: I^0-CPS, I^1-CPS, I^2-CPS, …, I^n-CPS, where I^0-CPS stands for the CPS without learning, I^1-CPS stands for the CPS with single-loop learning, I^2-CPS stands for the CPS with double-loop learning, and I^n-CPS stands for the CPS with *n*-loop learning.

The evolution of the CPS architectures from I^0-CPS to I^n-CPS, is presented in [23]. Figure 2 and Fig. 3 present the CPS models spectrum domain [23], and the Logical Architecture to model an I^n-CPS, i.e. an "*n*-loop" learning CPS (modified from [23]).

Considering the characteristics of the learning process and the *intelligent machine architecture* proposed, it is obvious that the human role is central in the *n*-loop learning CPS, i.e. in I^n-CPS. The position of the human in the architecture is presented in the Fig. 3 as well. It is important to notice that although the object, i.e. the 'physical' part of the manufacturing system, could perform totally automated, 'behind' always stands human.

So, total automation is only possible in a context in which the underlying architecture is abstracted, or when the human role is abstracted.

3.2. ON READINESS OF THE PRESENT TECHNOLOGIES AND KNOWLEDGE TO UPGRADE MANUFACTURING SYSTEMS TO I^n-CPS

This section presents a very short, and informal, review on readiness of some of the state-of-the-art technologies considered as constituents for the implementation of the I^n-CPS, in accordance with the model presented in Fig. 3.

The present journal (*Journal of Machine Engineering* (JME)) represents an excellent insight on the stat-of-the-art technology that represent a part of manufacturing I-CPS enablers. These technologies could be grouped by different criteria, of which one criterion is their functionalities such as (not exhaustively):

– *sensor technology* and the sensor embodiment with the machine tools for monitoring and transmission of machine tool organs, components or behaviour in real time. E.g. [25–27], that correspond to the module of acquisition and transmission of the "sensorial data" (detail "A" in Fig. 3);
– *simulation technologies* in order of prediction of behaviour and adequate decision making. E.g. [28, 29], corresponding to the prediction and simulation modules (detail "B" and "C" respectively in Fig. 3);
– *real-time control*, e.g. [30], which is the essence and a distinctive feature of any CPS, including the I^n-CPS, as a new control paradigm, and implicitly present, by the definition of the CPS, within the I^n-CPS architecture in Fig. 3;
– *AI applications*, e.g. [31], to embed the learning module in I^1-CPS in Fig. 3;
– *High-Performance Computation (HPC)*, as new processing capacity for sensorial data, e.g. [32], which represent a new computational paradigm that will probably substitute the actual one (small or disaggregated clusters), especially considering the new required computation, able to deal with the expected real-time processing

of huge amount of data (Big Data) streaming continuously from the thousands of sensors existing in manufacturing system equipment. That will probably one of the distinctive features of any CPS, including the I^n-CPS on Fig. 3;
- *low energy and narrowband communications* to support a massive number of low-throughput devices and lower energy consumption, critical requirements for IoT continuous data transmission support in CPS [33]. This capacity is assumed supported in the I^n-CPS on Fig. 3;
- *security, privacy, and integrity supporting technologies*, in order to assure the efficiency of IoT massive machine-type communications inherent to the CPS loop learning processes. This capacity is assumed implemented in the I^n-CPS on Fig. 3;
- *frameworks for development CPS subsystems*, such as the framework for "resilient and traceable on-machine measurements" [34] as a condition for building reliable and resilient CPSs, and building and integration of Internet-of-Things (IoT) for "utilisation of IoT and sensing for machine tools" [35], that identifies the "sensing items" for a machine tool. Another distinctive feature of any CPS, represented by multiple sensorial data channels and the corresponding feed-back loops represented on Fig. 3;
- *frameworks for development of "machine tool intelligence"*, or the intelligent machine tool, including the "Hardware-in-the-loop simulation for machine tool" architecture consisting the "physical device level" and the "virtual model", which is actually the main feature the CPS [36];
- *concepts for autonomous machines*, e.g. [37], requesting the same capabilities similarly to the "autonomous driving", and which could be interpreted as a form towards totally autonomous machine tools and manufacturing systems, and in the limit to the *manufacturing singularity*.

Considering the state-of-the-art of the CPS supporting technologies and the existing deep knowledge on those technologies, the readiness of the present technologies and knowledge to improve manufacturing systems towards I^n-CPS, could be evaluated as very high.

Surely, further research on the readiness is necessary, especially in the context of defining realistic roadmaps for development of the next generation manufacturing systems based on I^n-CPS. However, it could be expected, in a near future, a shift, if not an 'explosion', towards intelligent CPS.

4. AN EXPERIMENT

Several experiments were undertaken to evaluate the role of a human, as a teacher/oracle, and the influence of the learning algorithm type on the learning process.

As a demonstrator, an industrial case of a program for controlling a manufacturing cell was considered as the object system, i.e. the system to be learnt. Here, the program's function was to control automatic movement (transport and manipulation) of parts (i.e. pallets with the parts), within the manufacturing cell. Although the demonstrator (the manufacturing cell control program) is relatively simple, it could be said "elementary", it is sufficient to demonstrate the complexity of the problem and the role of human, especially as the paper's objective is not to solve a concrete technical problem, or class of these. Also, in the context of the human role demonstration, it is not relevant comparison of different learning algorithms, which would perform differently of course. However, the role of human will be always fundamental for any machine learning algorithm in some form, e.g. even in the case of unsupervised learning algorithms the human intervention is indispensable for various tasks, namely preparation of training sets, verification of the learned model as well as the quality of learning, etc.

The manufacturing cell, represented in Figure 4, consists of an input/output buffer with random access (*z*), three machines tools (*a*, *b*, *c*), and six input and output channels (one input and one output channel per machine). By "transport" of the parts we mean movement of the parts between the buffer and the input/output channels, and by "manipulation" of the parts we mean the movement of the parts from the transportation route to the machine and from the machine to the transportation route. Abstractly, the difference between "transportation" and "manipulation" is not relevant.

From the control program point of view, for our objectives, the routes or the trajectories the parts need to perform, are relevant, i.e. a part may need to have the following trajectory(ies): *buffer* → *machine_a* → *buffer*, or *buffer* → *machine_b* → *buffer*, or *buffer* → *machine_b* → *machine_c* → *buffer*, etc.

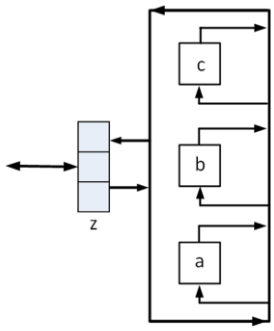

Fig. 4. Manufacturing cell demonstrator

The problem is to learn the program for controlling all possible routes/trajectories needed to produce all parts.

Synthesising the program by *learning* is synthesise of the program "by any means other than explicit programming" [38]. In the context of following the inductive inference based learning, specified in the Section 4.2 – Part I [22], it means that the learning is performed based on examples.

Thus, the application of the inductive inference based learning in this demonstrator, could be described as following:

If a unique symbol is associated to each element of the manufacturing cell, then the parts' trajectories could be described by the sequences of these symbols. Each sequence of the symbols is considered as a phrase, or a sentence. The set of all correct sequences of the parts' movements through the cell, i.e. sentences, constitute a 'language' that describe all valid programs for controlling the parts' movements within the cell. Formally, a language is described as the set of all sentences belonging to that language, or, in a more practical and shorter way, by the corresponding *grammar*. Here, the grammar is a set of rules that create or validate any sentence in the corresponding language(s).

In this way, inductive inference based learning of the program for controlling a manufacturing cell, could be represented as the learning of the corresponding language, i.e. learning the grammar that produces all particular programs for the parts' movements within the manufacturing cell, based on incomplete set of examples. In a formal way, repeating, we will say that "Inductive inference is automatic learning of formal grammars from finite subset of sentences from the language they generate" [39].

Based on the approach described above, four different experiments were realised in order to evaluate the performance of the learning algorithm originally developed, as well as to *demonstrate the human-role within the learning process*.

The first three experiments were already realised and presented in detail, i.e. the algorithm used, program developed as well as the examples and results obtained, in [40] and [41]. The fourth experiment was realised specifically in the context of this paper.

In the first three experiments the representation class used was a deterministic finite automata (DFA) and the corresponding regular language, or grammars.

The differences between the three experiments were in the learning algorithm applied, the types of examples, the use (or absence) of the oracle, the grammar produced, number of calls for oracle, as well as the oracles strategies, software implementation, and some others factors not relevant for the scope of this paper.

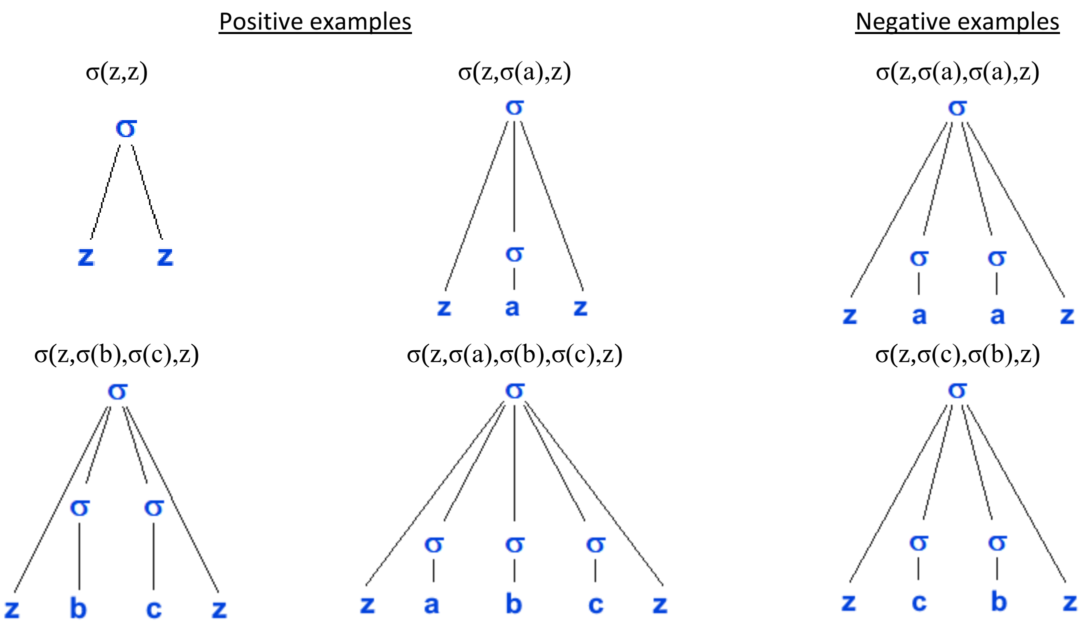

Fig. 5. Positive and negative examples structures for learning context-free grammars in the fourth experiment

Concerning the fourth experiment, the main qualitative difference from the three previous experiments was in using the representation class of *Context-Free Languages* (represented by *Context-Free Grammars*). This is a more complex representation class than regular languages (see e.g. [42]).

While the examples for learning regular grammars (or languages) are pure strings of terminal symbols, the examples for learning context-free grammars (or languages) are represented as tree structures (which are much more complex structures than sequential representation, i.e. regular sequences of symbols). Figure 5 shows the tree structures representations of examples for learning in the fourth experiment. The Greek symbol of sigma (σ) is used to represent internal/non-terminal nodes in tree structures.

To illustrate how much more complex task for oracles are in the case of learning in the class of context-free languages, an example of a hypothesis, for which the oracle should say is it valid or not, from learning organizational architectures of an enterprise is given in Figure 6 (the example was produced by the work in [43], for generating (learning) of the organizational architectures of an enterprise, in general, and in particular, for the BM_VEARM virtual enterprise architecture following [44]).

For such complex structures, the number of required interventions by the human expert (oracle) is huge, easily reaching up several thousands of queries. This problem requires some automation techniques to help the oracle. However, this is not relevant in the scope of this paper.

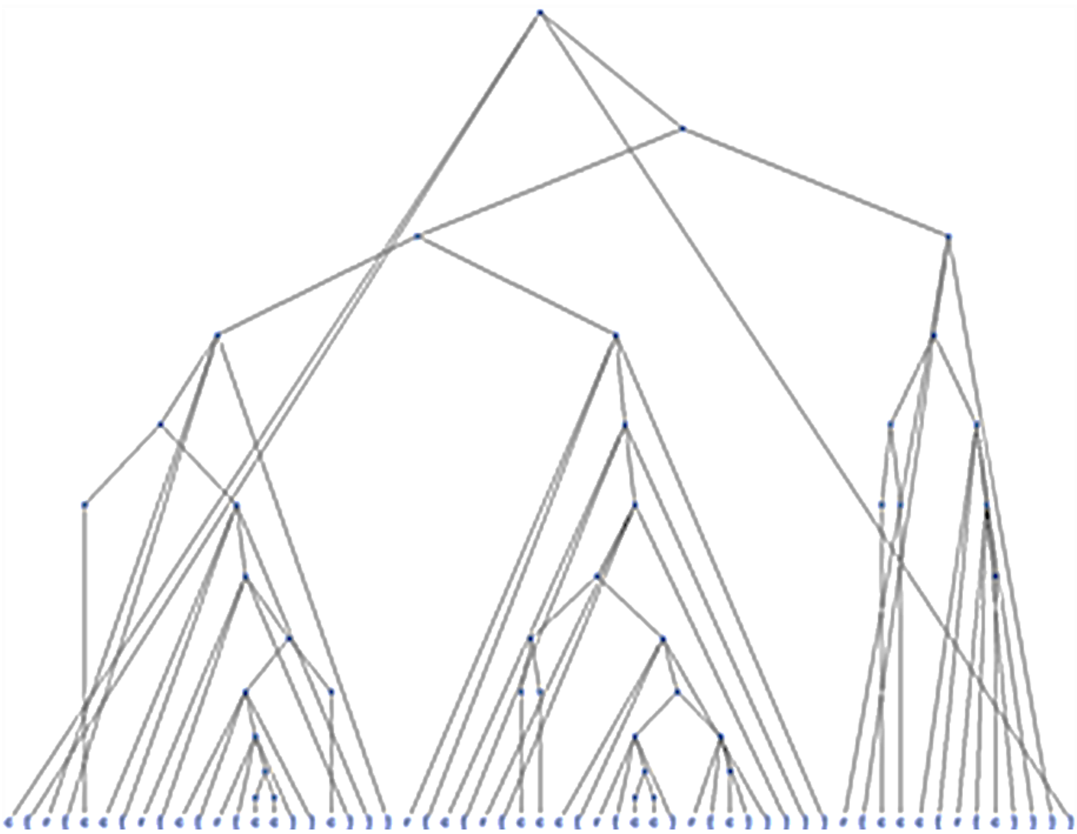

Fig. 6. A visualization of a phrase structural description, for context-free grammar inference task

Concerning the application of the learning algorithm in the representation class of context-free languages, in our demonstrator, the characteristics and results, comparing the first three experiments, as well as the fourth experiment, are given in Table 1.

Table 1. Comparison of the experiment's characteristics, outcomes and human participation

Exp. n°	*Ref.*	*Representation class*	*Algorithm*	*Type of examples*	*Oracle type*	*Number of production rules in the learned grammar*	*Number of calls for oracle*
1	[40]	regular language	Angluin's [45], [46]	positive only	human	110	142
2	[40]	regular language	Angluin's [45], [46]	positive and negative	human	16	146
3	[41]	regular language	Regular grammar synthesis [47], [48]	positive only	n.a.	12	n.a.
4		context-free language	Sakakibara's [49]	positive and negative	human	7	2148

As more details for the first three experiments are already given in [40] and [41], some characteristics of the learning process/algorithm performance as well as the produced grammar in the fourth experiment, are given below, Table 2 and Fig. 7 respectively.

Table 2. Performance of the learning process/algorithm in the fourth experiment of learning in the representation class of context-free languages

Execution Order	Input example/ counter example	Example type	Total tree combinations	Membership queries	Remark
1	σ(z,z)	Positive	3905	0	
2	σ(z,σ(a),z)	Positive	9330	19	
3	σ(z,σ(b),σ(c),z)	Positive	271452	275	
4	σ(z,σ(a),σ(b),σ(c),z)	Positive	177155	1854	
5	σ(z,σ(c),σ(b),z)	Negative	n/a	n/a	Example rejected
6	σ(z,σ(a),σ(a),z)	Negative	n/a	n/a	Example rejected
			461842	**2148**	

$$
\begin{aligned}
S &\rightarrow z\ z\\
N0 &\rightarrow S\\
N4 &\rightarrow a\\
S &\rightarrow z\ N4\ z\\
N2 &\rightarrow b\\
N1 &\rightarrow c\\
S &\rightarrow z\ N4\ N2\ N1
\end{aligned}
$$

Fig. 7. The grammar produced in the fourth experiment of learning in the representation class of context-free languages

The fourth experiment is also developed in the context of I^n-CPS architecture, but only in the context of the single-loop learning CPS architecture, i.e. for the I^1-CPS architecture, Fig. 8 [41].

Concerning the role of human as oracle or teacher in the experiments, we can observe very different results for the same problem depending on the type of human intervention. These differences have many reasons, but the main reason is human. The human role in 'guiding' the learning process is determinant for the output.

Even using the same software, if different human 'teacher' guides the learning process differently, the results will be different. Also, same human 'teacher', when running the learning process in different times, will apply virtually different guidance and the results will be different.

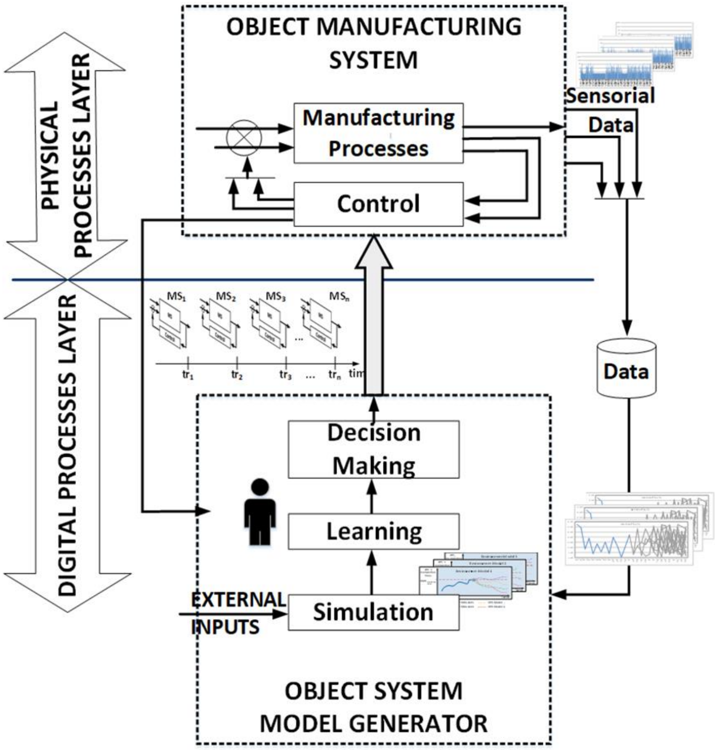

Fig. 8. The single-loop learning CPS architecture – I^1-CPS architecture as an instance of the *n*-loop learning CPS architecture – I^n-CPS (originally presented in [41])

The issue of 'how to guide the learning process', or 'what are the strategies for guiding the learning process', could have different approaches. Automatizing the oracle, learning from databases (also relevant for Industry 4.0 since such learning databases could be stored on cloud and part of Big Data), etc., are examples of approaches that apparently hide the human role. In the case of automatizing the oracle, in fact, the human is behind its programming (the experiments with this approach were already realized). Whereas in case of 'big data', where human might not be at the source of the data or information, it is up to the human to interpret the data/information, etc. It is not difficult to conclude that the role of human is fundamental. In other words, human is at the centre.

5. A VIEW FROM COMMUNITY ON AI BASED INDUSTRY 4.0 IMPACT ON JOBS

Apparently, the manufacturing community does not look so far to the state of the *upper* extreme, i.e. to the *manufacturing singularity* and to its extreme consequences such as total dominance of machines over manufacturing and economy, but to the scenarios closer to the *lower* extreme, implying the horizons within a decade or two.

Considering that there is no doubt that AI/ML will achieve, and very soon, very high degree of autonomy, from the social point of view, the problem is that any scenario apart from the "lower" extreme (which is without any significant effect), rises a number of fears, from individual to societal, e.g. from losing individual jobs to the fear of the automation, implying AI/ML, effect over part of economy concerning manufacturing, and consequently, over significant part of the social structure.

As it is easy to assume, that the view on the subject problem of this paper, by manufacturing engineers and scientists, is through the lenses of Industry 4.0 (I4.0) (although some of the I4.0´s main instruments, such as Cyber-Physical Systems, Internet-of-Things, etc., even didn't come from manufacturing), and how AI/ML will affect actual human work and participation in decision making. In other words, in the context of the measure we adopted, how AI/ML will affect actual human jobs, the thesis could be formulated as:

– *"The Industry 4.0 will destroy the jobs …"*, or its dual,
– *"The Industry 4.0 will create the jobs …"*.

Actually, there is a big discussion on the issue, as, apparently, and similarly to the question on AGI/ASI in the Chapter 2, there is no concrete answer, or any kind of proof. All answers, found in the literature, are based on statistical and forecasting analyses. Some say and argue that Industry 4.0 will destroy the jobs performed by humans, while others say totally opposite, that the Industry 4.0 will create new jobs.

There is a number of texts whose discourses are in favour of the thesis that the I4.0 will destroy jobs. For example, K.F. Lee (AI expert) claimed in his book [50] that "artificial intelligence will technically be able to replace around 40 to 50 percent of jobs in the United States". This evaluation was reported in the magazine Fortune [51] as well. In [52], the authors in fact agree with this view and call for attention to the significant negative effect on economy due to job losses because of robotics and AI. In [53] the author wrote "the overall consequence of using machines instead of people to produce goods and services will, of course, be unemployment" and that "It would be both foolish and tragic for us to slow our progress toward automation because of concern about unemployment" (The author further stands on the position that the world needs automation to enable "the transition from poverty, despair, and constant revolution and warfare to a more stable, just, and prosperous world society" implying necessary social and governance policies changes to compensate unemployment). In [54] the authors have similar position with a plead: "Rather than worrying about the risk of losing jobs to AI and robots, we must consider how the competition between those companies and people that can make effective use of AI and robots and those who cannot results in inequality". It is also important to refer to the findings by the authors that there will be heterogeneous effects of AI and robots in terms of skill levels, gender and regions, and that "active labor market policies to facilitate job mobility are necessary". In [55] the authors conclude, based on experts' evaluation, that "adoption of a GMI, along with an expected proliferation of new creative jobs, will keep unemployment at tolerable levels". As a measure to counterbalance unemployment "Muddling through would be a prudent way for humanity to proceed through the exponentially changing decades ahead".

Concerning the job profiles that will be affected by AI and robotics, the majority of authors refer that the negative impact of AI and robotics will be upon middle- and lower skills. However, there are authors that provide analysis which indicate that virtually all profiles could be affected, such as the analysis by [56] and others, depending on a number of factors.

Following findings, or opinions within the expert community, a number of magazines, that communicate news from technology and business for technology and business readership, but as well for the general public, published a number of articles with titles such as:

– "*How the robots will take your job and kill the economy*" (Fast Company, 2015) [57],
– "*Industry 4.0 will be a factor in 5m job losses in next five years*" (Drives&Control, 2016) [58],
– "*Automation could kill 73 million U.S. jobs by 2030*" (USA Today, 2017) [59],
– "*Job loss from AI? There's more to fear!*" (FORBES, 2018) [60],
– "*A third of manufacturers expect job losses due to Industry 4.0 advancements, finds Make UK study*" (British Plastics and Rubber Magazine, 2019) [61],
– "*Robots are stealing our jobs*" (Entrepreneur, April 2019) [62].

However, in the scientific literature, there could be found analysis with conclusions that the number of jobs lost will be less than the number of newly created jobs. In other words, loss of the jobs will not be so dramatic as the lost jobs will be substituted with new jobs, and that the total sum will be positive, e.g. in [63], [64].

The analysis in [63] "reveals how potential job loss due to automation in "applying" sectors is counterbalanced by job creation in "making" sectors as well in complementary and quaternary, spill over sectors."

The author in [64], sees the positive effect of AI and robotics through collaborative work of humans and machines (robots), i.e. "we are witnessing a new business and technology climate in which humans and robots are more likely to work together effectively, each playing a key role in performing a number of workplace tasks. They stated that humans are necessary to develop, train, and manage various robotic and artificial intelligence applications. To use Daugherty and Wilson's words, humans "are enabling those [robotic] systems to function".

These findings are accompanied by the reports by some international institutions and known consultancy companies.

For example, in the study by [65], published by the McKinsey Global Institute, a detailed study is presented by job types in different industry sectors. The study clearly concludes that the net jobs will be positive, e.g. for the personal computers and automotive sectors, the net jobs created will be 15.755 and 6.906 (in thousands) respectively, where the net jobs created are the difference between the jobs created and the jobs destroyed: "*Technology drives the creation of many more jobs than it destroys over time, mainly outside the industry itself*".

For example, World Economic Forum in its newer study [66] presents a review and evaluates that there will be a significant reduction in actual jobs, and jobs' profiles, while the new jobs and needs for new job profiles will be created. In total, the sum will be positive, i.e. I4.0 will be creator of net new jobs. This scenario implies "*agile lifelong learning, as well as inclusive strategies and programmes for skills retraining and upgrading across the entire occupational spectrum*". Further, there will be an opportunity for the so-called "augmentation strategy" referring to the new opportunities for the "business transformation" together with "skills retraining and upgrading across the entire occupational spectrum". (The media also reported these findings on positive effects of AI and robotics, in favour of the thesis that the I4.0 will create jobs, similarly to the news in media on opposite scenarios, e.g. for example: "*Industry 4.0 could create millions of new jobs*", (www: Futurithmic, 2019) [67]).

The authors in [68] recognise these differences "regarding the effects of robotisation and AI on productivity, employment and wages.", and that "both positive and negative scenarios could result from different economic structures with different economic specialisations. … This further implies that this process is time-sensitive and depends on the current stage of development in a country as well as its socio-institutional features." However, the authors conclude that "although robots will not completely replace the human workforce in the short run, the issue of labour dislocation must be addressed by targeted policies because of its negative effects on employment and wealth polarisation in our countries". Some negative effects in the short run are probable (or expected) "because robotisation seems to be growing faster than the capacity of workers to acquire new skills".

The above-referred reports that the "EIU[7] study also projects that employment in the manufacturing sector will remain relatively steady after AI technology penetration"

However, on the other side, the study by World Economic Forum [69], despite the fact that "over 2 percent of Americans, that is around 7 million people, lost their jobs in mass layoffs from 2004 to 2009. Many of these job losses were due to automation and manufacturing positions being moved overseas. While the larger mass of the populace enjoyed cheaper products, a good deal of American workers, mostly without college degrees, lost their careers" refers the conclusions by the MIT Review that: ""we have no idea how many jobs will actually be lost to the march of technological progress."".

6. CONCLUSIONS

The main theme of the paper is: will the new developments of AI/ML, and projected paradigms of AGI/ASI, totally exclude humans from decision-making? In support to answer to this question, a number of arguments from literature in favour and against are reviewed.

The authors' clear position against the possibility that the future development of AI/ML will exclude humans from the decision making is presented.

The Part I of the paper is focused on presenting the argumentation against the hypothesis that "advanced AI/ML, in the form of AGI/ASI, will totally exclude humans from decision-making in general," in addition to introducing manufacturing singularity as a reference value, and proposal of a general intelligent machine architecture. Whereas, the Part II is dedicated to more concrete issues of manufacturing.

[7] EIU: the Economist (magazine) Intelligence Unit

In this second part of the paper, four contributions are presented. First, a review of AGI/ASI in manufacturing and industry is given, showing that consideration of the AGI/ASI issues in manufacturing is only beginning.

Secondly, an architecture of an Intelligent Cyber-Physical System with *n*-loop learning, denoted as I^n-CPS, is presented. The architecture follows the 'general intelligent machine architecture' defined in Part I. Additionally, a short evaluation of readiness of the present state-of-the-art technology and knowledge is given, concluding that there exists a high level of readiness and that a shift, or even an 'explosion', of new generation of manufacturing systems based on I^n-CPS, of course, controlled by human, could be expected.

Thirdly, an analysis of a set of experiments is given, with the objective to quantitatively evaluate the role of human during the learning process, showing that an effective learning is not possible without human, which is one of the objectives of the paper. The example presented is that of a supervised learning algorithm, which obviously requires a human intervention to provide a labelled set of training examples. Nonetheless, even in the case of unsupervised learning algorithms the human intervention is indispensable for various tasks, namely preparation of training sets, verification of the learned model as well as the quality of learning. This is the case for a number of programs (algorithms) which apparently act without human intervention, such as chess and go programs, but in fact, the human is "behind". Also, all these programs (algorithms), that apparently act without human, belongs to so-called Artificial Narrow Intelligence (ANI) not capable to do anything else except narrow tasks for which they are conceived. Finally, as a fourth contribution, a review of industry 4.0 impact on society is presented, namely the impact on employment, especially considering growing applications of AI/ML based technologies, referring mainly to AI and robotics in 'taking jobs' from humans. Concerning the future work, from engineering point of view, the challenges are following. First, conception of a learning algorithm for learning other learning algorithm, i.e. "closing" and implementation of the 2^{nd} loop learning architecture, especially for the CPS for manufacturing, which is not known to the authors up to now. Second, understanding the intelligent machine architecture as a framework providing the directions of possible future research, as well as new research on designing more complex architectures that would include relationships other than the sequential, on the object system level, as well as including the relationship among the learning algorithms at all meta-levels and cross levels, creating a *n*-meta-dimensional learning network. Third, development of interfaces for integration of the existing technologies and knowledge constituents of new generation of manufacturing systems based on I^n-CPS, and of course, controlled by human.

Finally, the authors would like to conclude that we will have, for sure, an approximation to the scenarios of total exclusion of humans. This will be possible for the so-called 'physical part' of the manufacturing, but not for the so-called 'soft' part of the system. This situation will certainly imprint deep structural changes, technological as well as economic, and even political, that will surely increase importance of coupling engineering with social, ethical, humanistic and political issues.

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