Meta-learning for Enhancing Machines' Intelligence in Manufacturing

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Machine learning is usually considered a branch of artificial intelligence that enables machines (computers) to learn from data and improve their performance without explicit programming. The paper presents a review of research on meta-learning, also called double and semi-double-loop machine learning, based manufacturing. The paper provides a selected list of meta-learning definitions and generic models and discusses implementation architectures. Following, a set of meta-learning applications in manufacturing is presented, addressing three sub-domains: the basic „classical" processes in manufacturing systems, the manufacturing systems, including some advanced concepts such as smart manufacturing, advanced communication, and Industry 4.0, and manufacturing eco-system as a generic name for a number of application sub-domains that are directly or indirectly related to manufacturing and that could provide virtually easy knowledge transfer to manufacturing. In the last part of the paper, some future research and development directions are given.

Key Words: *machine learning, artificial intelligence, meta-learning, models, manufacturing*

1. INTRODUCTION

1.1. General Consideration on Artificial Intelligence

The intelligence of machines is a long aimed objective. If it could be traced very far ago, even in antique times, the modern approach could be related to Samuel Butler, who wrote in his essay in 1863, „Darwin Among the Machines“ [1]. In [1], Butler wrote, „The upshot is simply a question of time, but that the time will come when the machines will hold the real supremacy over the world and its inhabitants is what no person of a truly philosophic mind can for a moment question.“, which was later further developed in more details in „Erewhon“ (1872) [2], later cited also by A. Turing. And, of course, to the famous Turing's references, including his famous test of „machine intelligence“, in the year 1950, [3]. (See also [4], [5] for more discussion on the theme of „machine intelligence“).

Although „artificial intelligence (AI) and „machine learning“ (ML) today are virtually the most spoken theme in general, we should not forget that similar expectations were in years 80's-90's. In those years, 'in the "80s-'90s, there were expectations that the fast-growing computational power, in those years, would result in AI equal to the human brain, e.g. [6] in the series Proceedings on Artificial Life, edited by C. Langton. However, it didn't happen. (There were several reasons for that, which are not the subject of this paper, but to mention some: e.g., insufficient algorithms and globalization).

Concerning manufacturing, a great number of works were developed in the area of intelligent manufacturing, i.e, in the area of „artificial intelligence“ (AI) and „machine learning“ (ML) applications. A notable effort in this direction was the proposal of a global project on Intelligent Manufacturing Systems (IMS) promoted by H. Yoshikawa [7]. Independently of the management problems that the IMS project, in fact, disabled its global implementation, many of the work, including many papers and books, on AI/ML applications in manufacturing were induced by this idea.

In that (conditionally) „first“ historical period of AI and its applications in manufacturing, we witnessed the first AI „hype“, Figure 1. And the AI-based approach didn't result as expected (as already menti-oned above).

However, recent developments in computational power and „intelligent“ algorithms, together with the growth of global competitiveness, which led to the

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definition of new business and technological concepts, especially the concept of Industry 4.0 (I4.0), brought again into sight the possibilities of AI, resulting in seeing AI as, virtually, the main transformative instrument for a complete change of our society. E.g. in [8] is said that "Artificial Intelligence (AI) is set to fuel the Fourth Industrial Revolution". Of course, this expected transformative change would start with technological aspects of our lives, including manufacturing, up to the overall social context and organization. In that sense, it could be said that today, there is the 2nd AI „hype" (implying an „extended hype cycle diagram" or „double hype cycle diagram", in comparison with the original Gartner's diagram [GDP]), Figure 1.

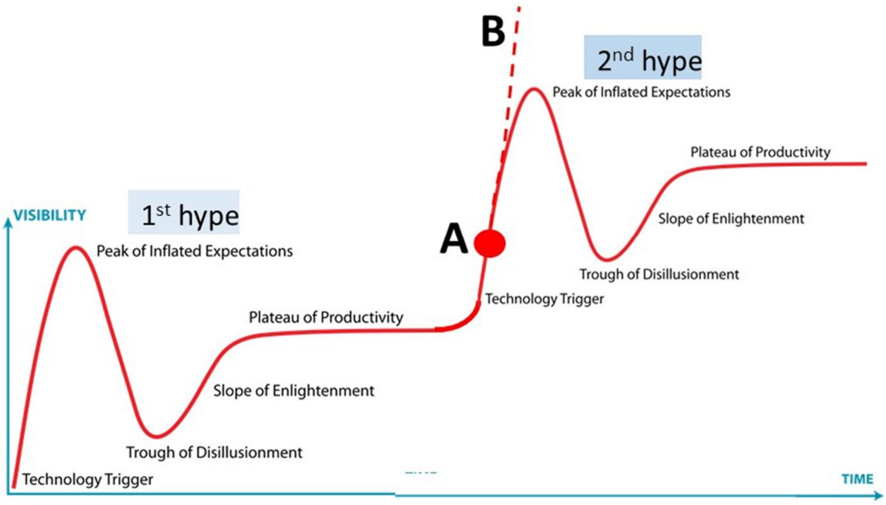

Figure 1 – Two AI "hypes"

The 2nd hype is a manifestation of suggestions, published in many popular, as well as scientific discourses, that expected future "massive" use of AI/ML, and especially its 'substantial progress' in so-called Artificial General Intelligence (AGI) and towards Artificial Super-Intelligence (ASI).

AGI is defined as intelligence equal to general human intelligence in any domain, hence strong AI, or human-level AI (until now, there was achieved AI only in specific fields, called Artificial Narrow Intelligence (ANI), or weak AI, that "could perform as a super-intelligence, but only in a narrow domain, e.g. in chess playing" [4], or, e.g. „in many specific applications in manufacturing, but totally impotent in other areas" (ibid.). ASI is defined by Bostrom N. [9] as „an intellect that is much smarter than the best human brains in practically every field, including scientific creativity, general wisdom, and social skills", and that could range "from a computer that's just a little smarter than a human to one that's trillions of times smarter" [10] (referring to human as individual or collective).

Concerning the developments towards AGI/ASI, some authors claim that AGI, whether in its initial phase or not, is already achieved, e.g., see [11] that says that „we must assume that AGI has arrived, regardless of how immature it might be. From a safety perspective, it may also be wiser to rely on false positives rather than false negatives in this context." Or it is to be achieved in 2026 or 2027, e.g. see [12].

Whether AGI or ASI, any of them could generate transformative changes „up to the total exclusion of humans from work and decision making, even generating the 'existential risks' for humanity" [4].

Looking at the "2nd hype" diagram, Figure 1, the immediate question would be: where are we now at the diagram?

The question is difficult to answer.

Considering that the left ascending part of the „hype" diagram has a lower part characterized by acceleration and a higher part characterized by deceleration, and considering that some authors and research policy influencers and policymakers, including the leading personalities from the technology sector, say that we are in the phase of accelerating of AI towards AGI, we could say that we are virtually at the point still on accelerating part of the „hype" diagram, denoted by the point „A" at the 2nd „hype" diagram. The continuation of the diagram could continue the acceleration, dashed line denominated by „B", or continue by deceleration by the full line.

Note that the diagram is a „logical" one, not based on some quantitative parameters and, therefore, not proportional. It means that the decelerating part of the curve could be much higher under the condition that Gartner's „hype" is true.

So, if we are in the acceleration phase of AI development, the question is how to contribute to this process, in particular, within manufacturing.

Although AGI development is based on Large Language Models (LLM), including deep learning and neural networks [13], the question is whether further development should follow the LLM and underlying techniques only. This is because maybe using other technologies or tools could be considered uncompetitive. E.g. [14] Amazon Web Services CEO said, „The technology is moving at an incredible rate … I don't know that we've seen technology progress as fast as it has. And I think one of the challenges of that is it's hard for everyone to keep up".

However, other authors, e.g., see [15], see that one of the development directions should address the improvement of learning algorithms in general, i.e., „Continued improvements in machine learning techniques will be essential for creating more adaptable and capable AI systems" [15].

Following the second approach, this paper aims at the promotion of meta-learning, or „learning about learning," as the contribution to the improvement of learning algorithms in general and, in particular, to manufacturing, i.e., to enhance machines' intelligence in manufacturing.

1.2. Meta-learning in bibliographic data

Meta-learning is a relatively new approach, although there have already been more than 20 years since the researchers started to consider meta-learning, or "learning about learning", in other areas, primarily in computer science and algorithms, while in manufacturing, the applications are much lesser.

Considering that meta-learning significantly improves the performance of the usually used learning algorithms, especially augmented autonomy of systems, simply because it represents „learning about learning" in an automated (algorithmic) way, the use of meta-learning in manufacturing is one of the development directions that should become one of the „standard" technologies.

To evaluate meta-learning as an emergent technology (tool), it is sufficient to look at the simple bibliographic statistics, referring to how many publications and their trends are published in the area of ML, referring to all application sectors and AI within the manufacturing sector alone. Then, these results will be compared with the application of meta-learning, referring to all application sectors and meta-learning within the manufacturing sector alone.

Looking at the bibliographic data, we could conclude that the applications of ML in manufacturing are significantly lesser than in all other sectors combined, which could be understood as the ML technology is, in fact, independent of a sector and considering the percentage of manufacturing participation in a totality of all other sectors. The same conclusion could be made in relation to meta-learning.

The Figures below show the statistics of publications within the SCOPUS database from 2004/2006 (for the majority of queries) to 2024, searching the titles, abstracts, and keywords for the abovementioned criteria.

The number of publications („documents") per year published in the area of ML referring to all application sectors, Figure 2, is obtained by the query:

```
query1: (TITLE-ABS-KEY(machine learning))
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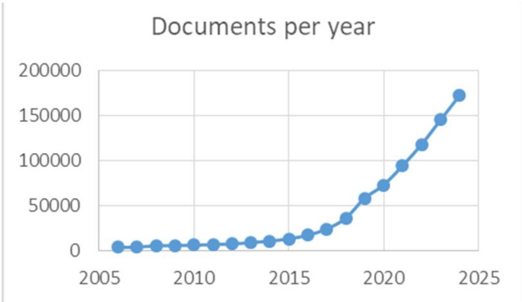

Figure 2 - The number of publications ("documents") per year published in the area of ML referring to all application sectors

The total number of publications for the query1 was 817.892 publications in the period of 2006-2024.

The number of publications („documents") per year published in the area of ML and manufacturing, referring to the manufacturing sector alone, Figure 3, is obtained by the query:

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query2: (TITLE-ABS-KEY(machine learning) AND manufacturing))
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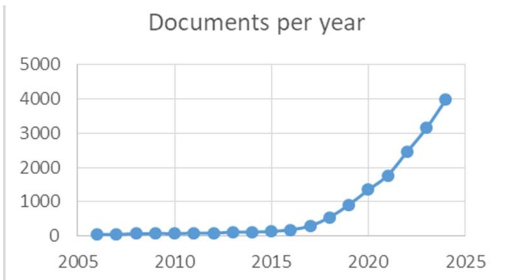

Figure 3 - The number of publications ("documents") per year published in the area of ML and manufacturing, referring to the manufacturing sector alone

The total number of publications for query 1 was 15.556 in the period 2006-2024.

Here, we should inform you that for the period 1996-2005, there were 551 publications, which shows that the idea of meta-learning was promoted much earlier but without acceptance by the research community.

The number of publications („documents") per year published in the area of meta-learning referring to all application sectors, Figure 4, is obtained by the query:

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query3: (TITLE-ABS-KEY (( meta-learning OR meta-learning ))
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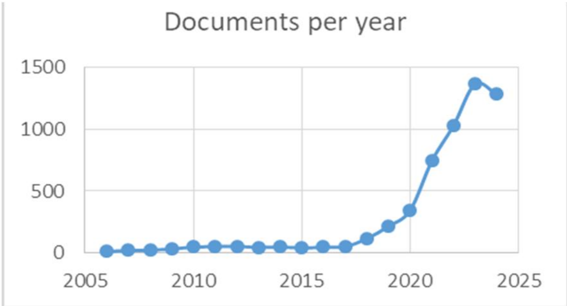

Figure 4 - The number of publications ("documents") per year published in the area of meta-learning referring to all application sectors

The total number of publications for the query1 was 5.585 publications in the period of 2006-2024.

Also, there were two forms of the meta-learning concept, i.e, „meta-learning" and „meta-learning", as both are used in publications.

The number of publications („documents") per year published in the area of meta-learning and manufacturing, referring to the manufacturing sector alone, Figure 5, is obtained by the query:

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query4: (TITLE-ABS-KEY ((meta-learning OR meta-learning) AND manufacturing))
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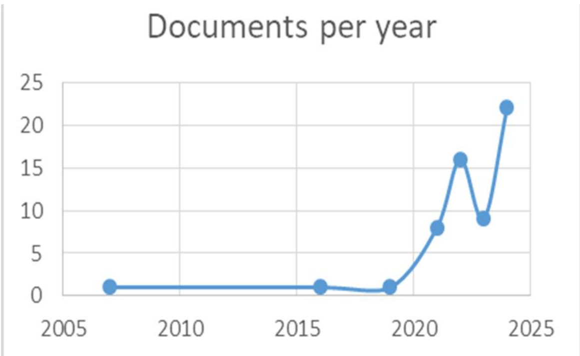

Figure 5 - The number of publications ("documents") per year published in the area of meta-learning and manufacturing, referring to the manufacturing sector alone

The total number of publications for query 1 was 58 publications only in the period of 2007-2024.

A small number of publications have appeared only in the last few years. This could be an indicator of the emergence of the use of meta-learning technologies (tools) in manufacturing, to which this paper aims to contribute.

1.3. Organization of the paper

The paper, further, is organized as follows:

The second chapter is dedicated to the question of what is meta-learning. There presented a number of selected definitions, which make a "spectrum". The third chapter gives a review of the meta-learning algorithms „exploitation" together with some of the implementation architectures. The fourth chapter refers to the applications of meta-learning algorithms in manufacturing, while the fifth chapter presents a logical architecture for the implementation of meta-learning. The sixth chapter presents some directions for future research and development, and the paper finishes with conclusions and references.

2. META-LEARNING DEFINITIONS

Meta-learning has a number of definitions in the literature. These definitions differ not only in wording but conceptually as well. In that sense, the definitions make a „spectrum". Identification of a „spectrum" is inspired by the classification of mixed reality models [16], which is applied as well to the „spectrum" of Cyber-Physical Systems (CPS) models, especially by criteria of existence of (machine) learning modules that at the one end consists of the CPS model with meta-learning [17].

It is necessary to say that in [17], instead of the term „meta-learning", the term „double-loop learning" is used (which will be commented more below). So, the terms „meta-learning" and „double-loop learning" should be considered synonyms, altho-ugh the term „meta-learning" could have a more com-plex connotation.

Table 1. presents a list of selected meta-learning definitions.

Table 1. Meta-learning selected definitions

Nº	Definition:
1	„Any form of learning from information about learning processes and models can be referred to as meta-learning." [18]
2	„Meta-learning, as applied to model selection, consists of inducing mappings from tasks to learners." [19]
3	„Meta-learning differs from base-learning in the scope of the level of adaptation: meta-learning studies how to choose the right bias dynamically, as opposed to base-learning where the bias is fixed a priori, or user parameterized." [20]
4	"In its broadest sense, it encapsulates all systems that leverage prior learning experience in order to learn new tasks more quickly [21]. This broad notion includes more traditional algorithm selection and hyperparameter optimization techniques for Machine Learning [22]." [23]

Nº	Definition:
5	„Meta-learning is a machine learning approach to explore the learning process and understand the mechanism of the process, which could be re-used for future learning. Compared to base-learning, which learns a specific task (e.g., credit rating, fraud-detection, etc.) on the corresponding data, meta-learning is a learning process that continuously gains knowledge as tasks being accomplished by the base-learners accumulate." [24]
6	„Domain experts use their knowledge regarding the performance of machine learning algorithms on previous tasks. Meta-learning imitates this strategy by accumulating the knowledge obtained from the application of algorithms on similar tasks and then using that knowledge to recommend a set of potentially appropriate algorithms for a specific task [25]." [26]
7	„Meta-reinforcement learning (meta-RL) is a family of machine learning (ML) methods that learn to reinforcement learning. That is, meta-RL uses sample-inefficient ML to learn sample-efficient RL algorithms or components thereof." [27]
8	„Meta-learning, or learning to learn, is the science of systematically observing how different machine learning approaches perform on a wide range of learning tasks, and then learning from this experience, or meta-data, to learn new tasks much faster than otherwise possible." [28]
9	„the algorithm selection problem is clearly a learning problem. The term meta-learning, 1 learning about learning, was first used in this context by [29] The algorithm selection problem can be formally stated as follows. For a given problem instance x ∈ P, with features f(x) ∈ F, find the selection mapping S(f (x)) into algorithm space A, such that the selected algorithm α ∈ A maximizes the performance mapping y(α(x)) ∈ Y." [30]
10	„approaches that handle the problem of model selection as a learning problem on the meta-level (meta-learning). Here, the goal of meta-learning is the construction of meta-models that associate dataset descriptions with algorithm performance." [31].
11	„Meta-learning is tightly linked to the process of acquiring and exploiting meta-knowledge. Meta-knowledge can take many different forms and can be defined as any type of knowledge that can be derived in the course of employing a given learning system" [32]
12	„Meta-learning differs from base-learning in the scope of the level of adaptation; whereas learning at the base-level is based on accumulating experience on a specific learning task" [33]
13	„The double loop learning model, conditionally denominated as the „canonical" model, implies two separate learning algorithms, in the first and in the second loop. … the learning algorithm in the second loop learns about the learning algorithm in the first loop, modifying not only its parameters' values but modifying as well the parameter set and the object-learning algorithm's structure, generating even a totally new learning algorithm in the first loop." [34]

Therefore, at the one end there, could be positioned a meta-learning system based on the existing knowledge of learning algorithms and considered, by the author of this text, as, conditionally, the simplest and not true meta-learning system, for example, the definition presented in the entry 1 in Table 1, while at the opposite end could be positioned a so-called canonical meta-learning system that generates a totally new, unknown, learning algorithm, for example, the definition in the entry 14 in Table 1.

3. EXPLOITATION

3.1. Meta-learning algorithm models

The idea of „meta-learning", i.e, of „learning about learning", could be modeled in virtually infinite ways. The models are very much influenced by several factors, among which are 1) our understanding of the learning process in general, such as individual, collaborative, etc. learning models by humans, see e.g. [35], to be transported to computer algorithms, and 2) the available computational machines, referring to their computational power to be used (e.g., intended, or available, use of a personal computer or a „super" computer) as well as their architectures (e.g. intended, or available, use of a single computer or a network of computers).

In the literature, review/survey papers that present a list of meta-learning models can be found, such as in [36]. However, a much larger number of papers present particular models. These publications usually present the models in more detail and usually with the model's validation, which is of particular interest.

In Table 2, a list of selected models is presented.

It could call attention to entries 2-3 in Table 2, referring to collaborative and federated models that resemble collaborative engineering models and federated models that resemble federated integration (e.g, enterprise) system architectures.

Next, entries 4-6 in Table 2 refer to reinforcement learning as a model of meta-learning directly after the "second-loop" learning model by Argyris C, e.g, in [37], which originally didn't have anything with machine algoritmization. Here, it would be necessary to note that some authors do not consider reinforcement learning as a true meta-learning but, at best, as a *semi*-meta-learning or *semi*-double-loop learning because of "the learning algorithm's behavior changes under the external (human) [GDP] input and under the policy changes, but without change of the agent's learning algorithm structure" [34]. Nevertheless, by the interpretation/definition in entry 1, Table 1, which is the most inclusive, reinforcement learning could be considered as a meta-learning model.

Also, the model presented by [38] refers to PAC (Probably Aproximate Correct) learning theory by Valiant L, see [39], [40], in a formalized way, namely its refined model PAC-Bayes theory, which gives a rigorous theoretical base for quantitative evaluation of the learning process.

Finally, it would be necessary to consider combinations of „single“ models, such as entries 2, 3, 5 in Table 2, all in order to improve the performance of the „single“ models.

Table 2. Meta-learning algorithm selected models

Nº	Model:
1	„Deep meta-learning“ [23]
2	„Collaborative Learning Framework via Federated Meta-Learning“ [41]
3	„Federated learning personalization via model agnostic meta-learning” [42]
4	„Meta-reinforcement learning (meta-RL)“ [23]
5	„Human-level control through deep reinforcement learning“ [43]
6	„Meta-learning in Reinforcement Learning“ [44]
7	„Adversarial Meta-Learning“ [45]
8	„Continuous Meta-Learning“ [46]
9	„Lifelong learning and inductive bias“ [47]
10	„Modular meta-learning“ [48]
11	„Online Meta-Learning“ [49]
12	„Meta-learning by adjusting priors based on extended PAC-Bayes theory“ [38]
13	„Parallel and Distributed Learning by Meta-Learning“ [50]
14	„Formal Metareasoning Model of Concurrent Planning and Execution“ [51]

3.2. Meta-learning generic applications

Concerning meta-learning „generic“ applications, these are called „generic“ as the „building blocks“ for the development of applications in other sectors than computer science (similarly as in CAD systems, the geometric entities point, line, surface, volume are generic resources for building the product models in a variety of sectors).

A selection of these applications is presented in Table 3. These address the generic application for selecting time series models, time series forecasting and forecast combination, Intrusion Detection in Cyber-Physical Systems, Decision-Tree-Induction, Data Mining, Noise detection, Personalizing Dialogue Agents, Concurrent Planning, and Execution.

There are other specific generic applications, but the purpose of this list is just to address the generic dimension of meta-learning.

Entry 3, Table 3, „Intrusion Detection in Cyber-Physical Systems,“ could be considered within manufacturing, as Intrusion Detection in Cyber-Physical Systems (CPS) is one of the main constructs of Industry 4.0, in particular when referring to manufacturing. However, CPS has a much wider application domain than manufacturing.

Also, entry 9, in Table 3, is already referred to above within the models as the publication refers to both dimensions.

Table 3. Meta-learning selected generic applications

Nº	Generic application:
1	„Meta-learning approaches to selecting time series models“ [52]
2	„Meta-learning for time series forecasting and forecast combination“ [53]
3	„Unsupervised Intrusion Detection in Cyber-Physical Systems“ [54]
4	„Meta-Learning-in-Decision-Tree-Induction“ [18]
5	„Meta-Learning to Support Data Mining“ [55]
6	„Meta-learning for Scalable Data Mining“ [56]
7	„Noise detection in the meta-learning level“ [57]
8	„Personalizing Dialogue Agents via Meta-Learning“ [58]

3.3. Implementation architecture

As it is known, any model could be implemented in different ways. Thus, the implementation architecture, in principle, doesn't depend on the meta-learning model. This means that one meta-learning model could have a different application architecture. And vice-versa, one meta-learning implementation architecture could serve for two or more models.

In some cases that could be considered special cases, a meta-learning model is in a direct and unique relationship with the implementation architecture.

The implementation architectures constitute the datasets, which represent the input in any learning algorithm, and the learning algorithms. Next, the implementation architectures define how many are of these elements, e.g, data sets subdivided into subsets, one or more algorithms, and how these elements are connected, e.g., in sequence, in parallel, combined, etc.

One very good representation of these architectures is given by [54], in which publication of the architectures are called „approaches“ or „schemes“. Nevertheless, we will call them "architectures". [54] refer to the following architectures/approaches/ schemes: „bagging, boosting, stacking (generalization), cascade (generalization), delegating, arbitrating and (weighted) voting, which build the pool of possible meta-learners for model combination according to [their] literature review“.

Figure 6. presents the architectures/approaches/ schemes by [54].

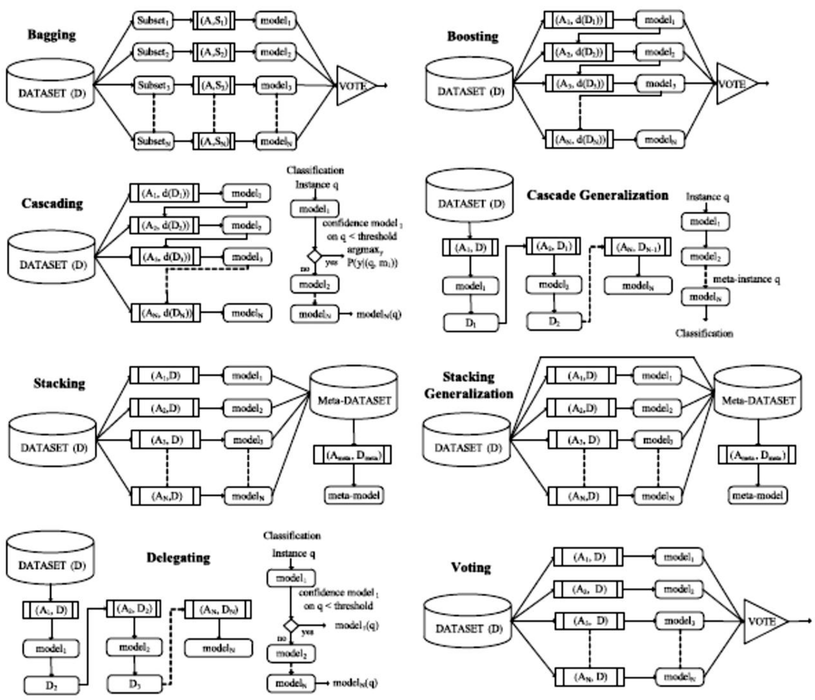

Figure 6 - Meta-Learning schemes, showing source dataset (eventually partitioned into subsets Si or derived datasets Di), algorithms Ai, and the models Mi they learn, for Bagging, Boosting, Stacking (Generalization), Cascade (Generalization), Delegating and Voting algorithms [54]

4. META-LEARNING AND MANUFACTURING

Manufacturing is a multidimensional domain. There are many possible "classifications" of the manufacturing sub-domains.

In [59], there are referred 4 subdomains:

- Basic manufacturing processes in a „classical" manufacturing system scheme, Figure 7, such as product development (design), process planning, production planning and scheduling (ERP), machining, assembly, maintenance, shipping, after-sale service, recycling, and remanufacturing, following the manufacturing lifecycle, Figure 7, but also particular functions that integrate the previous „global" functions such as machine vision, costs, quality, big data analytics, system degradation and upgradation, and others.
- „higher" structures of manufacturing systems and processes, combining several, or many, „classical" manufacturing system schemes, Figure 7, in new „constellations", moving from understanding the manufacturing system as a single business unit or enterprise (also used the term "monolithic" enterprise) to a network of independent enterprises (the terms used are network(ed) enterprises, virtual enterprises, and similar, among which one of the most popular is so-called supply chains, that could be understood as a simpler form of the networked enterprise)
- When saying „higher" structures, it can not be ignored the higher enterprise structures, apart from the basic technological processes referred above, that address business processes in the first place, such as (manufacturing development) strategy (which could define the circular economy, and/or innovation, as a goal towards sustainability), education and human resources management, accounting, auditing, marketing (by some considerations marketing could belong to the „basic" processes as a sub-function in the product development (design) phase), but also some logistic processes as energy efficiency and sustainability.
- Advanced manufacturing concepts, which are created by integrating additional information and decision-making structures and devices, building the concepts of smart manufacturing, see Figure 7, for enhancing the manufacturing lifecycle model with the smart objects that have multiple functions such as identity, sensing, decision making, actuation and connection to the communication network. Within the context of this paper, it is important to understand that the decision-making module is the model where AI/ML and, consequently, meta-learning are embedded. Based on these capabilities, other concepts are built, such as cognitive and predictive manufacturing systems, service-based manufacturing systems, customized manufacturing, zero-defect manufacturing, secure manu-

facturing, and finally, sustainable manufacturing as the overall goal of all improvements, etc. Also, within this „class", other manufacturing system concepts could be created by extension with specific equipment, such as robotics, additive manufacturing, and reconfigurable manufacturing. Finally, a number of strategies led us to the concepts of green manufacturing, customized manufacturing, secure manufacturing, etc.

- a variety of manufacturing sectors besides the „traditional" metalworking industry, referring to applications of manufacturing in the food industry, biotechnology industry, pharmaceutical industry, software industry, textile industry, automotive industry, semiconductor industry, process industry, and others.

Considering the above „classification", in this paper, we will address 2 sub-domains: the first is on manufacturing „processes", and the second is joining „higher structures" and advanced manufacturing concepts in the sub-domain „systems". Also, as there are many more applications in non-manufacturing (general) engineering that could be easily transported to manufacturing, as well as the manufacturing applications in the non-metalworking domain, these sub-domains could be joined under the name of „manufacturing eco-systems", which will be left to address for some future opportunity.

I.e. the sub-domains addressed in this paper are:

1) classical manufacturing processes,

2) manufacturing systems,

4.1. Meta-learning in „classical" manufacturing processes

Applications of meta-learning models in manufacturing „basic" processes, i.e, in a „classical" manufacturing system scheme, will be referred to following the sequence of processes as presented in Figure 7 (there could be other sequences, including some other processes).

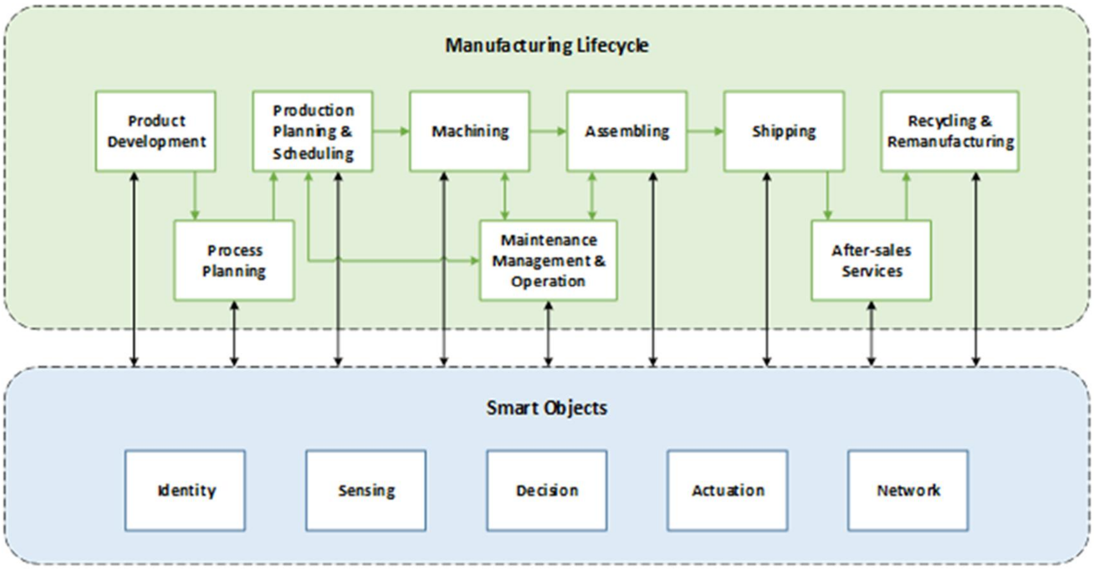

Figure 7 – Basic processes in manufacturing systems

The first process is product development or design. However, it is not found, or there are very few, direct applications of meta-learning for this domain, probably because the design doesn't provide data sequences (e.g, the data sequences of the cutting force or chatter, etc.).

Nevertheless, one example could be the case, referring to „robust chipping prediction", that could be understood as a part of chip design, referred to in [60]

The second process, Figure 7, is process planning. Although there were no applications using the name „process planning", this activity could be considered the activity on machining sequencing. Examples of meta-learning applications to this problem are referred to in [61].

Another case that could be classified within the process planning processes is the case of tool path optimization of five-axis flank milling, referred to in [62].

Production planning and scheduling follow the process of planning. In this sub-domain, it could be referred to the work by [63]. The work by [64] addresses remaining useful life (RUL), which is a modern parameter for production planning and scheduling. Following, the work by [65] is referred to. Although the work by [65] includes the maintenance planning, through the concept of integrated production and maintenance planning, it presents well how the meta-learning, i.e. „including the meta-learner for failure prognostic selection", improve these activities.

Concerning the machining processes, the works by [66] and [67] refer to „meta-reinforcement learning of machining parameters" by the criteria of energy efficiency, and to „chatter detection method based on meta-learning", respectively. Other works address the problem of tool wearing and monitoring as one of the most important parameters of machining. This issue is referred to in [68], [69], [70], [71], [72], [73].

Also, [74] which use simulation for identification of machining parameters (deformation).

The next process to address is maintenance. This is virtually the manufacturing sub-area with a very high number of meta-learning applications. The applications to maintenance management and operation come through applications to identify the state of particular elements of machine tools (and other industrial equipment). One of these elements is bearings. Although the experiments and the content of some research are bearings as general machine elements, including the design of these, the results are, in fact, applicable to maintenance. The works by [75], [76], [77], [78], and [79] refer to bearings state identification, i.e, fault diagnosis and monitoring.

Another group of papers refers directly to maintenance as in [34] that refers to predictive maintenance, and the group of papers addressing fault identification, or diagnosis, machinery health prognostics, and anomaly detection, see e.g. [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], and [91].

Although fault identification or diagnosis, machinery health prognostics, and anomaly detection could be classified in the group of production management as the faults could be from other reasons than the machine failure, it is decided to be considered within the maintenance. In concrete cases, it would be necessary to see which context is of the primary importance: faults from the production management side or from the machinery faults side.

The last sub-domain referred here, although not presented on Figure 7, is the sub-domain pof inspection and quality control. In this sub-domain, we also have a number of applications (although not so much as for the case of regular learning applications).

The references address the problems of surface quality to quality management. Examples of the research realized are presented in [92], [93], [94], [95], [96].

4.2. Meta-learning in Manufacturing Systems

The application of meta-learning algorithms in the sub-area of (manufacturing) systems is very diverse, as this sub-chapter covers 1) „traditional" manufacturing systems, such as Flexible Manufacturing Systems (FMS), and 2) advanced concepts such as Industry 4.0, Cyber-Physical Systems (CPS), smart manufacturing and cognitive manufacturing systems, but also the supporting infrastructures without which the modern manufacturing systems could not operate, such as 3) 5g communication, industrial big data, edge computation systems, Internet of Things (IoT) and sensorial systems, also, 4) energy system management as one of the most important infrastructural and operational subsystems, especially in nowadays struggle for sustainability, 5) robots (or robotics), as specific manufacturing devices, and 6) „higher" levels of manufacturing systems management such as costs management, knowledge engineering.

Following a list of meta-learning application references is presented in Table 4, related to the applications of meta-learning in the subsystem referred to above:

It is necessary to say that some works address the phenomena that could be classified in the above sub-chapter, on „basec" processes, such as [97], [98], [99], [100], [101] and some others, but it is decided to be included in this sub-chapter as these references refer to these phenomena within the concept of "systems".

Table 4. A list of meta-learning application references related to specific sub-domains

Nº	Subsystem	Reference
1	Flexible Manufacturing Systems (FMS)	[102]
2	Industry 4.0 (I4.0)	[103], [97]
3	Smart manufacturing	[104], [105], [98], [99]
4	Cognitive manufacturing network	[106]
5	Cyber-Physical Systems (CPS)	[107]
6	Supply chain	[108]
7	Edge Computation systems for Manufacturing	[109]
8	5G communications	[110], [111],
9	Internet of Things (IoT)	[112]
10	Industrial big data	[113]
11	Sensor system	[114], [115], [116], [117]
12	Energy	[118]
13	Robots	[100], [101], [119], [120]
14	Cost	[121]
15	Knowledge engineering	[122]

5. LOGICAL ARCHITECTURE

The meta-learning logical architecture should satisfy the definitions of meta-learning. From Table 1, we saw that the definitions form a spectrum, where, as said above in Chapter 2, at the one end, there could be positioned a meta-learning system based on the existing knowledge of learning algorithms, and considered, while at the opposite end could be positioned a so-called canonical meta-learning system that generates a totally new, unknown, learning algorithm, for example, the definition in the entry 14 in Table 1.

In Figure 8 [34], a logical architecture is presented that satisfies both ends of the definition spectrum and, in that way, could also satisfy the intermediate models.

As there are two loops, other names that could be used are 1) the "single-loop" learning for the system / architecture with the first loop only, denoting that there is only a „regular" learning about the object system model, and 2) the „double-loop learning" for the system/architecture with two loops, denoting that there is a meta-learning module too.

Further, the presented logical architecture has two „branches".

The right „branch" satisfies the meta-learning models in accordance with the definition given in entry 1, Table 1, providing an algorithm in the second meta-loop for selecting the best algorithm in the first loop. It could be said that this „branch" of the architecture is an approximation to the „canonical" model or a kind of 'primitive' meta-learning.

However, as this approach is based on the known learning algorithms, without the capacity to create new algorithms, [34] this approach is not considered a true meta-learning approach, calling it a "semi-double loop learning or „semi-meta-learning".

The left „branch" of the architecture is corresponded to the „canonical" meta-learning approach, where the learning algorithm in the second loop is capable of generating a totally new learning algorithm in the first loop, unknown until that moment.

The presented architecture has virtually all the elements needed for the implementation of the meta-learning. It has the sensorial system, which belongs to the object functioning, which behavior we want to learn, detail „A" in Figure 8, and that provides the input dataset, detail „B". Further, on the „left" branch, there is a module that generates a control module of the object system (e.g, machine-tool in manufacturing system), detail „C", in the first loop, and that could change along the time or could be different for each particular object system, as shown in [34]. Following, in the second, meta-, loop, there is a modul with the meta-learning algorithm, which, in the case of the right „branch", selects the best learning algorithm, from the repository of the known or available learning algorithms, for the case, detail „D".

On the left „branch", on the contrary, in the second loop, there is a meta-learning module capable of generating a totally new learning algorithm. The algo-

The architecture is composed of two „loos", i.e. feedback loops, in a hierarchical relationship, the first loop with the learning algorithm for the object system model generation, i.e. with the „regular" learning module, while in second loop represents a meta-learning, with the learning module but which improves the learning module in the first loop, i.e. the module that "learn about learning", hence the attribute „meta".

rithm in this module is, therefore, called „canonical" second-loop learning or „canonical" meta-learning.

Finally, the important condition for the existence of meta-learning is the feedback from the learning module in the first loop to the meta-learning module in the second loop. The adequate feedback relations provide this, detail „E" in Figure 8.

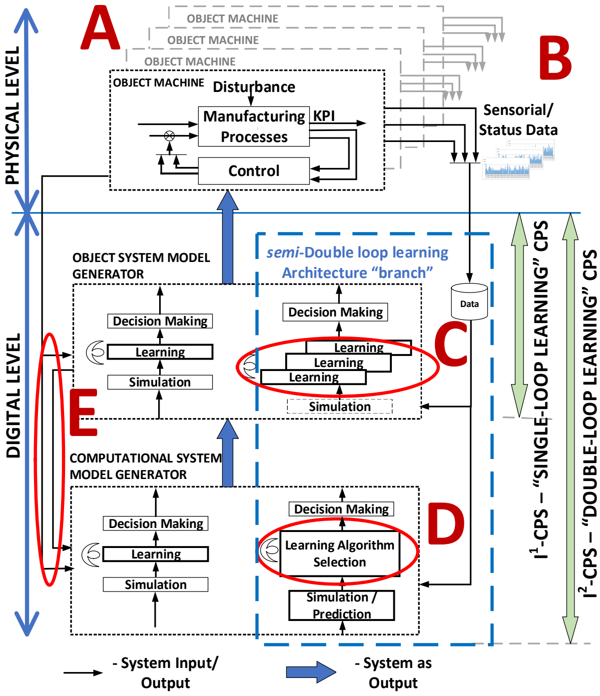

Figure 8 - Meta-learning, or double-loop learning logical architecture, applied for intelligent CPS (I^2-CPS) architecture, with canonical meta-learning or double-loop-learning „branch", and with semi-meta-learning or semi-double-loop learning architecture „branch" [34]

Figure 8 shows the architecture applied for CPS, a new control paradigm, which is one of the most important constructs for Industry 4.0 and which has sufficient generality for applicability in any industrial system.

It is important to recognize that the presented logical architecture doesn't address any implementation solution, being „open" for different application solutions, some of them in accordance with the archite-ctures presented above in Figure 6.

6. SOME FUTURE RESEARCH AND DEVELOPMENT DIRECTIONS

Future research and development directions are seen in several dimensions. The first dimension is technological, which implies improvement of the actual algorithms and supporting machines (computers and communication networks), and the second is related to the use of the developed technologies, considering the acceptance and spread of technologies as well as some social issues, of which the most discussed at the moment is the issue of working places, third is ethical which question the mode of use, and fourth could be the end future.

In this paper we will refer mainly to the first dimension and shortly to other dimensions that are implied within the technological one.

Concerning future research and development directions, we could refer to:

6.1.„Canonical" meta-learning model

This task is virtually the most difficult, as up to now, there is no knowledge, by the author of this paper, of any model or their implementation. Virtually all models, or a very large majority of these, could be classified as semi-meta-learning models or semi-double loop learning models. Fortunately (or not), by many definitions, all these models could be classified as meta-models.

One of the conditions is that the "canonical" meta-learning algorithm shall be capable of generating a totally new, not non-existent, learning algorithm. This condition is very difficult as the meta-learning algorithm should have the human capability of innovation.

The question is how to address the development of the „canonical" meta-learning model.

At the moment, there are just some ideas that could be considered as the starting hypothesis for the research, and later development that virtually in the future will be totally different than the actual „starting hypothesis".

First, one of the directions implies defining the algorithm's formal grammar. If this were defined, then the existing algorithms could generate the learning algorithms, among which a totally new one could be generated. Of course, it is not the question to generate any „totally new one", as there could be trivial solutions not of interest, but to generate „totally new one" that would be better (in performance) than the known learning algorithms.

Another approach is to use algebraic models of the learning algorithms instead of the formal grammar of the algorithms.

In both approaches, the meta-learning algorithm would generate instances of the learning algorithms in alphabetical order and compare their performance with the performance of known algorithms.

Anyway, this research implies a fundamental research.

6.2. n-level meta-learning, or n-loop meta-learning architecture model

If the 2-level meta-learning architecture, or double–loop learning architecture, is conceived, by induction, we could require that the meta-meta-level, i.e, 3-loop learning, would be defined, and, further, *n*-level meta-learning architecture, or *n*–loop learning architecture, is conceived.

This type of architecture is shown in Figure 9 [5]. If it is managed to realize the task of defining the „canonical" meta-learning algorithm, the task of defining the *n*-level meta-learning architecture, or *n*-loop learning architecture, should not be too difficult.

Another question is how many levels, 3, 4, or more, would be sufficient, or are necessary, to achieve the goal.

Similarly to Figure 8, Figure 9 shows the architecture applied for CPS, but without loss of generality concerning meta-learning in general. On the other side, if the main concern in this paper is manufacturing, CPS is one of the main constructs of the actual modern manufacturing systems and of Industry 4.0, as already referred to.

6.3. „Substantial progress" in Artificial General Intelligence (AGI) towards Artificial Super-Intelligence (ASI) – and artificial brain project

As AGI/ASI is defined above, in Chapter 1, we would say here that the research and development of meta-learning algorithms necessarily tend towards AGI/ASI (just to remind, as referred above in Chapter 1, AGI is already achieved, or, by more „conservative" evaluation, is to be achieved in just a couple of years).

Achieving AGI/ASI, especially ASI, is a very controversial issue. Its consequences could be the phenomenon called „trans-humanism", as the transitory phase, towards „post-humanism". Although these questions are not easy to answer, both „trans-humanism" and „post-humanism" could mean the end of the human race; see for further [4], [5].

Development towards AGI/ASI is related to two phenomena: the „singularity" and the Fermi paradox. The „singularity" says that there is a (singular) point after which the development of AI (including learning and meta-learning algorithms) becomes autonomous, totally without (our) human control. Of course, we would like to control this point, but the Fermi paradox shows that we can not know where the point of singularity is. (For a discussion and more references, see, e.g, [4] and [5].

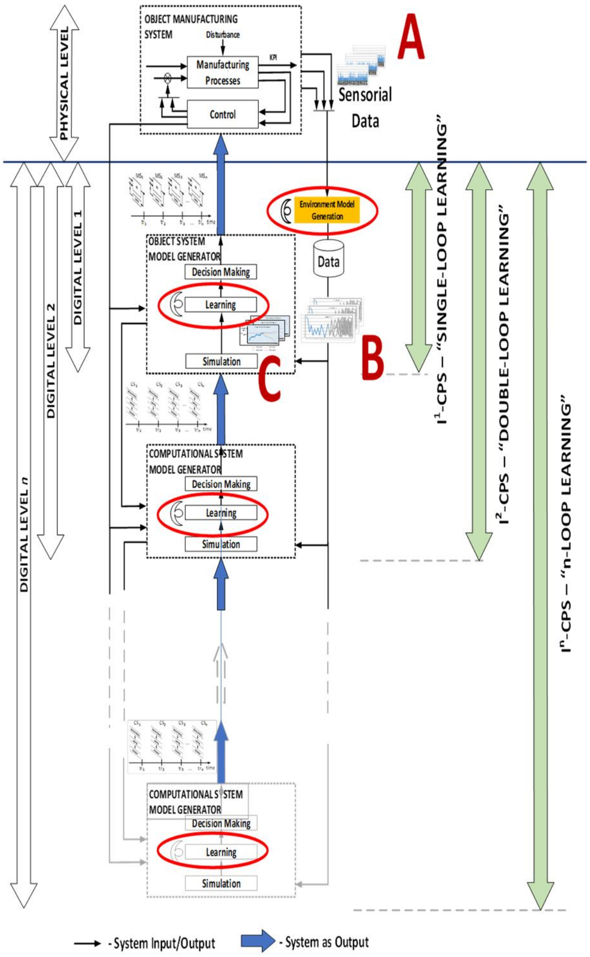

Figure 9 - Logical Architecture to model a n-level meta-learning, or n-loop learning (in-CPS) [5]

Although the ultimate goal of achieving AGI/ASI is criticized in [4] and [5] as impossible, the features of AGI/ASI could be considered legitimate because these could serve as reference values.

Approaches to these goals are also multiple.

It is worth to mention the series of the Conferences on Artificial General Intelligence (AGI), the first held already in 2008 [123].

Another important project is the project on artificial brain [124], [125], [126], also discussed in [4], [5].

The supposition is that if the center of human intelligence is the brain, then if we build the artificial brain, that device would have human intelligence, i.e., the device would have AGI.

The first steps are already made.

We will refer here to the project on robot control by brain signals (already a few years ago), see e.g. [127], Figure 10. (Boeing and the National Science Foundation financed the project).

The second is the project on the brain implant, Figure 11. The brain implant „electrically stimulates, blocks or records (or both record and stimulate simultaneously) signals from single neurons or groups of neurons (biological neural networks) in the brain.“ (https://en.wikipedia.org/wiki/Brain_implant)

The future is, of course, controlling the whole production system by an artificial brain.

6.4. Manufacturing singularity

Concerning manufacturing, the concept of manufacturing singularity is introduced in [4].

Similarly to singularity in ASI, the manufacturing singularity means the point (of AI/ML development)

Figure 10 - The feedback system enables human operators to correct the robot's choice in real time. After [127]

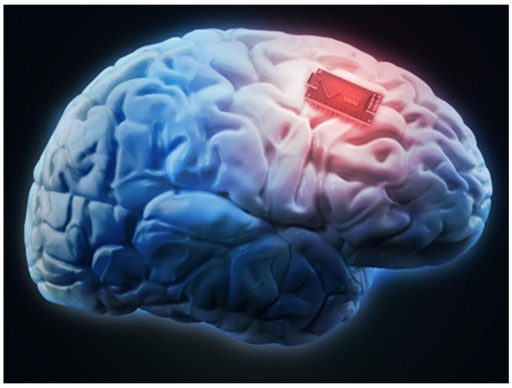

Figure 11 - Artistic presentation of the brain implant (source: https://spectrum.ieee.org/the-human-os/biomedical/ethics/the-ethics-of-using-brain-implants-to-upgrade-yourself)

After this, the manufacturing system would be totally autonomous, meaning that the manufacturing system would make all decisions totally autonomously, even on what to produce, etc.

At that point, the main problem would become social/ethical for the manufacturing community and for our society.

However, as for AGI/ASI, although our opinion is that achieving the manufacturing singularity is not likely, its definition is important because it would serve as a reference value.

In order to define the manufacturing singularity as a reference, future work would imply defining the whole set of the manufacturing functionalities and measuring approximation to it by the learning algorithm, i.e, what percentage of these functionalities are achieved as totally autonomous.

6.5. „Massive" use of AI/ML

„Massive" use of AI/ML as a goal is a necessary condition to achieve the AGI/ASI, particularly in manufacturing and manufacturing singularity.

While the applications of learning algorithms, i.e, of single loop learning, are already relatively numerous, the applications of meta-learning are very low in number.

However, considering the results of meta-learning applications in other areas/sectors, an increase in the number of meta-learning applications in manufacturing is expected. For this purpose, virtually, it would be necessary to 1) make a „catalogue" and classification of all functionalities of a manufacturing system and 2) to define some kind of „roadmap" in order to undertake this task in an organized way.

6.6. Democratization of AI, meta-learning inclusive

„Democratization of technology refers to the process by which access to technology rapidly continues to become more accessible to more people." (https://en.wikipedia.org/wiki/Democratization_of_te chnology). It is necessary to say that many sectors and technologies are going towards democratization or are already democratized. E.g, the democratization of energy, HPC, simulation, digital manufacturing, etc., see [128]. The question is if the meta-learning should be democratized.

There are several arguments in favor of the democratization of AI/ML development.

First, today, the most advanced AI/ML applications are proprietary, i.e., controlled mainly by companies from „Silicon Valley". Apparently, these companies lead the AI/ML developments against, say, universities (which are mainly financed by public funds). The question is, is it permissible? This is a social, economic, strategic, political and/or conceptual question.

Second, if the development of AGI/ASI in the future will lead to trans- and post-humanism, that is not desirable at all, how to control it, especially if the development is under proprietary control, i.e, under the control of some multinationals.

Third, the very recent events in AI/ML development strategy, showed by the first time that an open source application from China outperformed the applications form the „silicon valey" (we refer here the known case of DeepSeek vs ChatGPT).

So, in conclusion, AI/ML, including meta-learning, should be democratized.

One of the ways of „democratization" is to promote so-called „open source" within the „open X" philosophy, see [129], [130].

(Please note that the question of democratization of meta-learning is an open question, and the author just expresses his personal opinion.)

7. CONCLUSIONS

It could be verified that the use of meta-learning in manufacturing is at the very beginning.

All application of meta-learning in manufacturing systems, including all this development, is in fact towards total automation, i.e. total autonomy. Total autonomy means the exclusion of humans from production. This seems totally opposite to the so-called Industry 5.0, which promotes human-centric manufacturing systems. However, we claimed that, in fact, any development of AI/ML, including meta-learning, is not possible without human participation (this is presented by the human icons next to the learning modules in architectures in Figures 7 and 8); see [4]. In that sense, all results within Industry 4.0, including meta-learning-based applications, are possible only with human participation. (Therefore, the concept of Industry 5.0 is questionable, as their main features are already present within the concept of Industry 4.0. However, this issue is out of the scope of this paper).

Nevertheless, considering the results of meta-learning use in the applications in manufacturing already achieved, and especially the results in other sectors, it is possible to recommend, and to expect, its applications virtually for any manufacturing system functionality.

This could be consider specially taking into account the overall goals of achieving AGI/ASI, independently of their reality, but at least in terms of the reference values AGI/ASI, and in particular manufacturing singularity, could represent.

This is surely related to the question of quality control of the developments in the direction of AGI/ASI and towards the manufacturing singularity.

The paper presented the basic notions of meta-learning and its application, together with a proposal of a logical architecture for meta-learning-based systems, in particular manufacturing systems, and CPS architecture as one of the most important constructs for advanced manufacturing, including Industry 4.0. The proposed architecture was already applied with great success, see [34].

Also the paper presented some directions for future developments which are believed that could represent an input for defining future projects.

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РЕЗИМЕ

МЕТА-УЧЕЊЕ ЗА ПОБОЉШАЊЕ ИНТЕЛИГЕНЦИЈЕ МАШИНА У ПРОИЗВОДЊИ

Машинско учење се обично сматра граном вештачке интелигенције која омогућава машинама (рачунарима) да уче из података и побољшају своје перформансе без експлицитног програмирања. Рад представља преглед истраживања о производњи заснованој на мета-учењу, такође названим двоструко и полу-двоструко машинско учење. У раду је дата одабрана листа дефиниција мета-учења, генеричких модела и архитектуре имплементације.

У наставку је представљен скуп апликација за мета-учење у производњи које се баве трима под-доменима: основним „класичним" процесима у производним системима, производним системима, укључујући неке напредне концепте као што су паметна производња, напредна комуникација и Индустрија 4.0, и еко-систем производње као генерички назив за бројне под-домене апликација које су директно или индиректно повезане са производњом и које би могле да обезбеде практично лак пренос знања у производњу. У последњем делу рада дати су неки будући правци истраживања и развоја.

Кључне речи: *машинско учење, вештачка интелигенција, мета-учење, модели, производња*