INTELLIGENT CYBER-PHYSICAL SYSTEMS FOR MANUFACTURING

ИНТЕЛИГЕНТНИ САЈБЕР-ФИЗИЧКИ СИСТЕМИ ЗА ПРОИЗВОДЊУ

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Abstract: The paper referred shortly to applications of Artificial Intelligence and Machine Learning (AI/ML) in manufacturing. The paper is structured in three parts: the first part provides a general review of AI/ML in manufacturing, the second part presents the Cyber-Physical Systems (CPS) as one of the main constructs of manufacturing systems within the Industry 4.0 characterized by use of AI/ML, together with an example of AI/ML based CPS efficiency. The third part presents some possible future developments related to manufacturing, especially in the con-text of prevised, by many authors, future AGI and ASI (Artificial General Inte-lligence, and Artificial Super Intelligence).

Key Words: Artificial Intelligence (AI), Machine Learning (ML), Manufacturing, Applications

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Резиме: Рад укратко приказује примене вештачке интелигенције и машинског учења (ВИ /МУ) у производњи. Структуриран је у три дела - први део даје општи преглед ВИ /МУ у производњи, други део представља сајбер-физичке системе (СПС) као један од главних елемената производних система у оквиру Индустрије 4.0 коју карактерише употреба АИ/МУ, заједно са примером ефикасности СПС базираних на АИ/МУ. У трећем делу су представљен неки елементи будућег развоја у вези са производњом, посебно у контексту трендова претпостављених, од стране многих аутора, будућих АГИ и АСИ (Вештачка општа интелигенција и вештачка супер интелигенција).
Кључне речи: Вештачка интелигенција (ВИ), машински учење (МУ), производња, примене

1. Introduction

Artificial Intelligence and/or Machine Learning (AI/ML) is/are nowadays one of the few most popular themes in the technology developments, seen as the main instruments to achieve the „sustainability" (where „sustainability" is, in fact, seen mostly as the concept for keeping the concurrency, considering that „sustainability" has a number of definitions).

Manufacturing is just one of the numerous fields that are objects of AI/ML applications.

To recognize the AI/ML applications in manufacturing, it is necessary to consider other terms that implies the use of AI/ML. These terms are „intelligent" and „smart". I.e. the terms „intelligent manufacturing" and „smart manufacturing", and their derivatives, could be considered as synonyms for AI/ML applications in manufacturing.

This paper presents some aspects of AI/ML applications in manufacturing only, although some future developments would present some more advanced SI/ML approaches not so regularly found in the most of the literature. Further, the paper presents the issue of AI/ML in manufacturing through the Cyber-Physical Systems (CPS) as virtually one of the most important constructs of the manufacturing system within the concept of Industry 4.0 and that implies the use of AI/ML.

The paper is further organized as follows: the second chapter presents a shorter review of the literature concerning the use of AI/ML in manufacturing, the third chapter gives an introduction to CPS, or when referred within the manufacturing or production systems Cyber-Physical Production Systems (CPPS), and the fourth chapter presents just a few of the results of AI/ML applications efficiency in manufacturing in order to illustrate its potential. The fifth chapter presents some possible future developments of AI/ML with reference to manufacturing. Finally, the paper finishes with short conclusions and the list of references.

2. The role of AI/ML in manufacturing

Concerning AI/ML in manufacturing, there could be different „schemes", or frameworks, on how to present the role of AI/ML in manufacturing. For example, in (Plathottam, S. J, et al, 2023), a framework is presented, given in Figure 1, that considers four global layers: 'learning paradigms, 'learning models/techniques', 'learning tasks' and 'manufacturing industrial application'. Considering, further, that the first three layers are of general concern of AI/ML theory, and not specific to manufacturing, which are supposed to be discussed in other type of papers, this paper will present mainly a review of application in manufacturing ('manufacturing industrial applications'), except in some specific cases not sufficiently referred in the general and manufacturing oriented literature (such as "double loop machine learning").

A brief view on the literature on AI/ML applications to manufacturing, could identify two global groups of papers: the papers reviewing AI/ML in manufacturing in general, and the papers reviewing AI/ML in some specific fields of manufacturing covering different „dimensions" of manufacturing, some of them (the „dimensions") referring to management and education for AI/ML applications in manufacturing.

Examples of the literature addressing AI/ML in manufacturing in general, including intelligent and smart manufacturing, are:

- (Nti I. K, et al, 2022), (Mypati O, et al, 2023), (Li B. H, et al, 2017), (Hassani I. E, Mazgualdi C. E. & Masrour T, 2019), (Jan Z. et al, 2023), (Yao, X, et al, 2017), (Lee J, et al, 2018), (Wuest T, et al, 2016), (Rai R. et al, 2021), (Kinkel S, Baumgartner M. & Cherubini E, 2022), (Gao R. X, et al, 2024). The last one, (Gao R. X, et al, 2024), is one of the most recent and virtually most comprehensive concerning the „classical" manufacturing.

The papers reviewing AI/ML in some specific fields of manufacturing covering different „dimensions" of manufacturing usually refer to

- basic, „classical", manufacturing processes, such as scheduling, mainenance, machine vision, costs, quality, big data analytics, ERP, system degradation and upgradation, and others.
- „higher" structures of manufacturing systems and processes, such as supply chains and enterprises, strategy (of manufacturing developments), energy and resource efficiency, circular economy, education, innovation, human resources management, accounting and auditing practices, marketing,

- advanced manufacturing concepts, such as cognitive manufacturing, predictive manufacturing, robotics, additive manufacturing, green manufacturing, reconfigurable manufacturing, service industry, customized manufacturing, zero-defect manufacturing, sustainable manufacturing, secure manufacturing, etc.

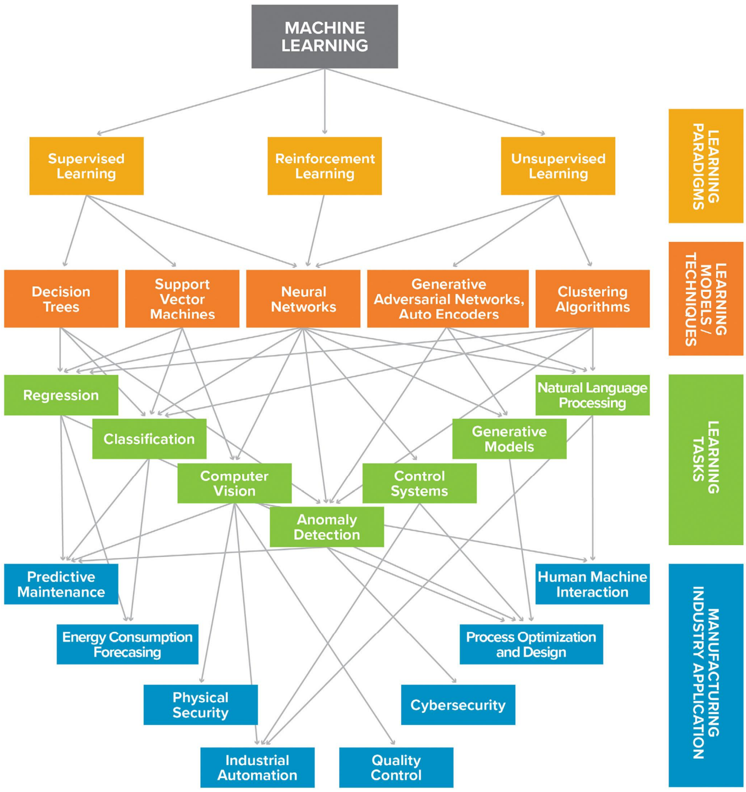

Figure 1. Common categories for various aspects of AI/ML applications in manufacturing. After (Plathottam, S. J, et al, 2023)

and in a number of manufacturing sectors, not only the metalworking industry, e.g: food industry, biotechnology industry, biopharmaceutical industry, drug industry, software manufacturing, textile manufacturing, automotive manufacturing, battery manufacturing, semiconductor manufacturing, process industry, material sciences, and other.

3. Cyber-physical systems in manufacturing

The first question could be „Why special attention to Cyber-Physical Systems (CPS)?”. The answer lies in the fact that CPSs are one of the most important constructs of advanced manufacturing, especially within the concept of Industry 4.0. CPS, or when referred within the manufacturing or production systems Cyber-Physical Production Systems (CPPS), are considered a new paradigm of control systems, see e.g. (Putnik G. D, et al., 2019), (Putnik G. D. 2021).

However, it is necessary to take into account the existence of a number of definition what is CPS (CPPS). In (Putnik G. D, et al, 2019) is given a list of definitions that range from relatively simple models of CPS, we could call them „reductionists' models" to models that, in our opinion, makes a truly new paradigm. In other words, there is a „spectrum" of definitions, Figure 2., ranging from the „classical" control paradigm, presented in Figure 3a, through CPS without learning (denoted as I^0-CPS or CPS^0), Figure 3b, and CPS with (single-) loop learning (denoted as I^1-CPS or CPS^1), Figure 3c, to the paradigm characterized by the double-loop learning, i.e. by the meta-learning (denoted as I^2-CPS or CPS^2), presented in Figure 3d.

The differentiation feature is exactly in the existence of the „ (machine) learning" module, i.e. in the existence of AI/ML applications to decision making. While the CPS^1 already include „learning", and therefore it is an „intelligent" CPS, i.e. with AI/ML implemented, this model still does not satisfy the CPS definition given by (Lee, E. A, 2008) which states that CPS are: „Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa (...)". The feature „where physical processes affect computations and vice versa" is fully satisfied only in CPS2 architecture. It implies the existence of a „meta-learning" layer, in other words „second-loop learning", that is capable to change the learning algorithm in the first loop.

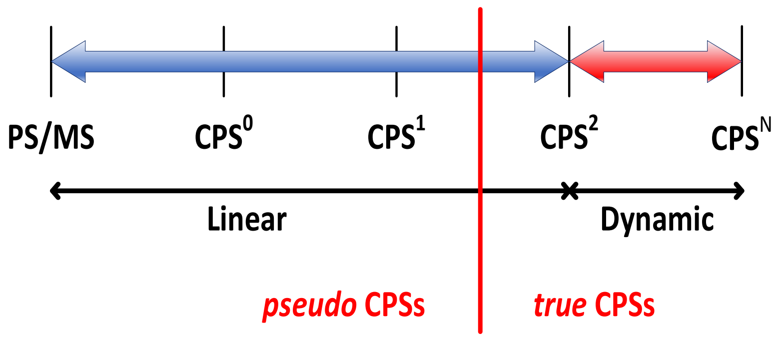

Figure 2. CPS definitions and models spectrum. After (Putnik G. D, et al, 2019)

Intelligent CPS, starting with the architectures with single-loop learning – CPS^1, are widely developed using the learning algorithms already indicated in (Plathottam S. J. et al, 2023) above, referred in the layers 'learning paradigms, 'learning models / techniques', and 'learning tasks' for a number of applications. Following the architecture schemes in Figure 3c, an application of CPS[1], for manufacturing control system, is presented in (Shah V. & Putnik G. D, 2019), which uses the inductive inference learning algorithm for synthesizing formal grammar as a model of the production line process control in the given context.

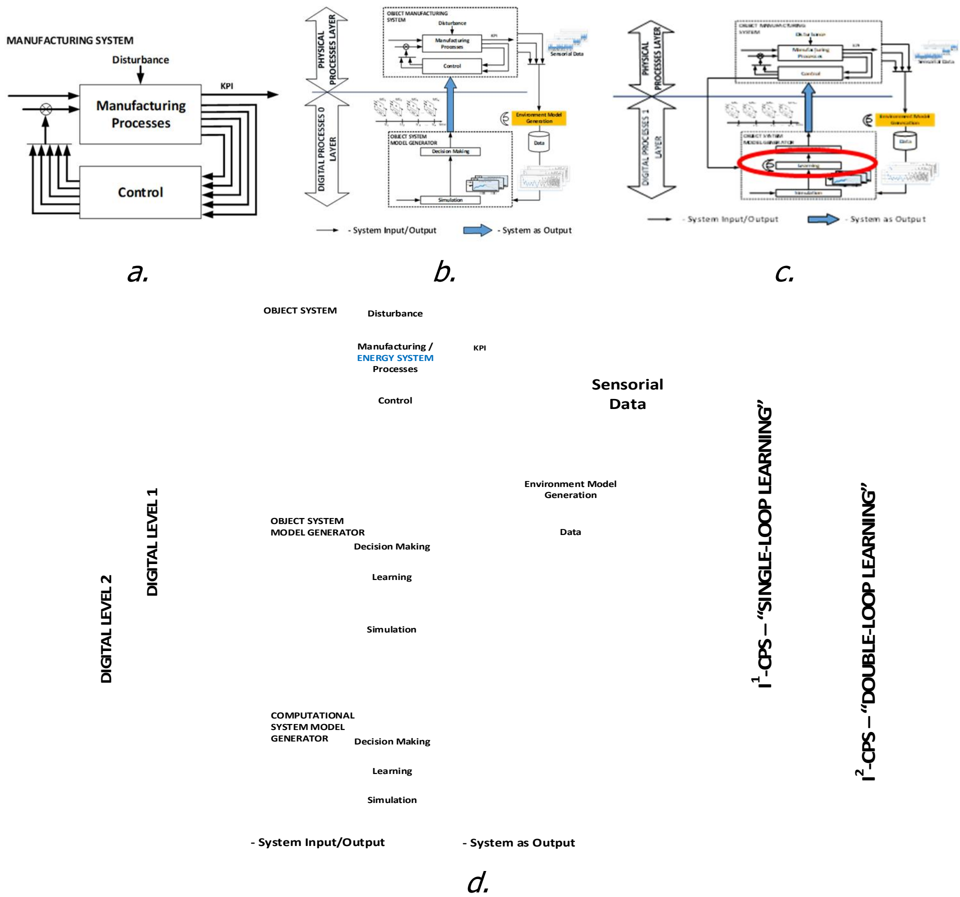

Figure 3. CPS logical architectures: a. Logical Architecture of the „classical" Production or Manufacturing System control system, b. Logical Architecture to model a CPS⁰, c. Logical Architecture to model a CPS¹, d. Logical Architecture to model a CPS². After (Putnik G. D, et al, 2019)

Concerning the architectures of the type CPS², true CPS², i.e. the true canonical meta-learning algorithm, is difficult to implement. Canonical CPS² means that the learning algorithm in the second loop is capable of generating a totally new learning algorithm not known until now. Until today there is no knowledge of such „canonical" models or implementations, neither in theory nor in applications. Instead, the first approximations are made through the selection of the best learning algorithm in the context.

Although this approach is in accordance with the definition of „meta-learning", e.g. see (Grąbczewski, K., 2014) in which the meta-learning is defined as „any form of learning from information about learning processes and models can be referred to as meta-learning.", we considered it as a *semi*-double loop learning, or *semi*-(canonical) meta learning.

An example of *semi*-double loop learning CPS architecture is presented in Figure 4 (Putnik G. D, et al, 2019), in which by the letters A, B, C, D, E are indicated the components of the CPS.

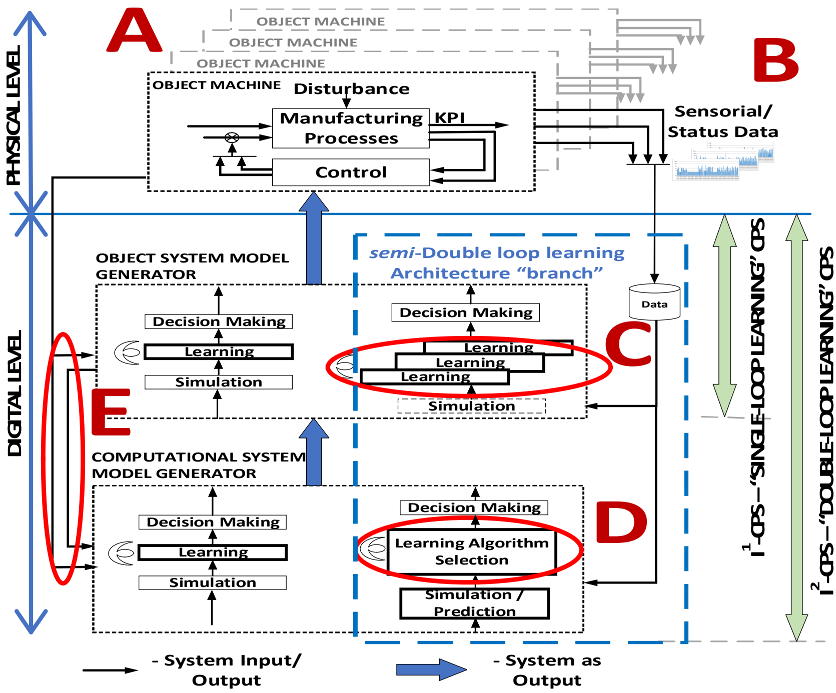

Figure 4. Double-loop learning intelligent CPS (CPS²) architecture, with semi-double-loop learning architecture „branch". After (Putnik G. D, et al, 2019)

4. On efficiency of ai/ml in cyber-physical systems in manufacturing

Efficiency of AI/ML applications in manufacturing systems is demonstrated in a big number of papers.

Here, as an illustration of AI/ML applications efficiency, the case of application of the *semi*-double loop learning in real-life industry is presented, with extraordinary results.

The example is presented in detail in (Putnik, G. D, et al, 2021), while here are rewritten just the main results for the purpose of illustration. The application predicts the maintenance operation for the second group of machines presented in Figure 5.

There were selection among the 8 learning algorithms, in the second learning loop: Support Vector Machine (Cubic, Quadratic with higher box constraint level), Random forest (1k & 100k learners), Naïve Bayes, Ensembled Learning (Bagged Trees and Logit Boost) and Decision Trees, and 3 strategies *details are given in (Putnik G. D, et al, 2021))

In Table 1 the list of the learning algorithms with the best performance per machine, after selection, are presented. It could be recognized that different algorithms perform best, for different machines, and with different performance. For performance measures the F1 measure are used, which are the "standard" measures for evaluation of learning algorithms.

The results obviously justify the use of the (*semi*-)second-loop learning, or meta-learning, models.

5. Some future developments

The future development of AI/ML applications in manufacturing should be considered for two periods: the first period refers to the „near" future, and the second period to the „far" future (although some say that that „far" is not so far…). A discussion on this issues are already presented in a great number of papers, e.g. see (Putnik G. D, et al, 2020) and (Putnik G. D, et al, 2021) which present a review.

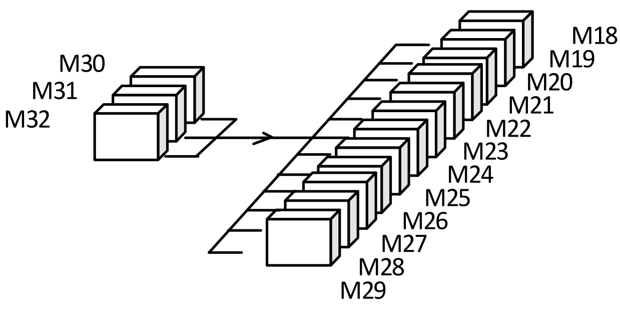

Figure 5. Schematic layout of the manufacturing plant

Table 1. Learning algorithms that output the best prediction of maintenance requirement, for each individual machine under Strategy 3, for either 3, 4 or 5 months training. After (Putnik G. D, et al, 2021)

Machine ID	**Algorithm**	**max F1 score**
18	SVM Cubic	0.8571
19	SVM Quadratic with higher box constraint level	0.8571
20	Ensembled Bagged Trees	0.8000
21	SVM Cubic	0.8000
22	SVM Cubic	1.0000
23	SVM Quadratic with higher box constraint level	0.7826
24	SVM Cubic	0.8000
25	Decision Tree	0.7273
26	SVM Quadratic with higher box constraint level	0.8000
27	SVM Cubic	0.8000
28	Ensembled Logit Boost	0.7619
29	SVM Quadratic with higher box constraint level	0.8000

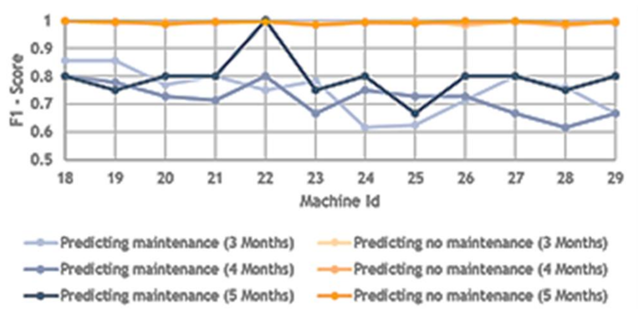

Figure 6. F1 score of predicting the maintenance when required, and of predicting no maintenance required, for each machine ID for the Strategy 3 and the algorithm in Table 3

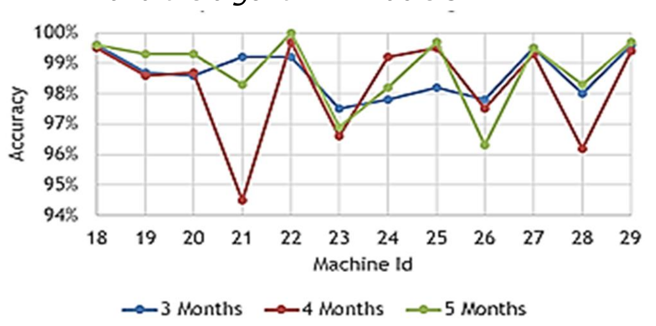

Figure 7. Overall accuracy of individual machine maintenance prediction for each machine ID for the Strategy 3 and the algorithms in Table 3

Concerning the „near" future, virtually the two most important issues are 1) the issue of jobs – losing jobs or opening new jobs, and security – the protection of personal and industrial data. These issues imply the integration of social sciences in manufacturing, which would change the actual „engineering thinking" which is the only thinking in actual engineering.

In the context of AI/ML technology itself within manufacturing, the „near" future developments would have several „trajectories". Some of them are related to further development of intelligent CPS, i.e. the future development beyond CPS^2 towards CPS^n, i.e. *n*-loop learning algorithms, which will mainly depend on success of development of canonical CPS^2 algorithms and architectures.

Further, facing the „big data" generated by CPS, and the evaluation of multiple scenarios within the predictive approach (for which we actually expect the contribution of AI/ML), there is a question of the actual computing technology in manufacturing companies (which is basically „personal computing"/servers based, with some use of cloud technologies) have enough computational power to face the new demands in data processing. This question implies developments in the use of High Performance Computing (HPC) (popularly called „super-computers", including quantum computers) as the standard future computational technology.

The last issue to refer to in this paper is the issue of large and complex open production networks, consisted of thousands, or hundreds of thousands and virtually millions of participants. These networks are considered impossible to design and/or control, due to their openness and complexity. However, in the last research presented in (Putnik G. D, et al, 2024), it is shown that in fact it is not a complete true. It is shown that these networks are possible to design and control, for which one of the possible instruments is the introduction of virtual agents.

Therefore, the issue of virtual intelligent agents is one of the challenges for the future development of AI/ML applications in manufacturing.

Concerning the „far" future, the developments of AI/ML in manufacturing should be seen within the AGI and ASI (Artificial General Intelligence, and Artificial Super Intelligence) approaches. AGI refers to the intelligence equal to the human general intelligence, while ASI refers to the intelligence that over-passes many times, in principle up to „million" times, the intelligence of one human or of the whole human race (see (Putnik, G. D, et al, 2020) and (Putnik, G. D, et al, 2021) for a discussion in the context of manufacturing). These concepts, AGI/ASI, are related to two phenomena: singularity and Fermi paradox. Singularity refers to the „point" after which the development of AI/ML becomes totally autonomous, independent of human intervention, that in the limit leads to „trans-humanism” and „post-humanism”, and in the extreme to possible extinction of human race (therefore AGI/ASI represents a threat to human race – according to many authors). From the other side the Fermi paradox refers to human impossibility to recognize the singularity point, and therefore the human is incapable to intervene.

In this context, manufacturing has a number of directions in which the development is possible. Here, we will refer to two directions that seems to us as to the most indicative.

The first is the project of Artificial Brain. The idea behind is that if we manage to construct, and build, it, then the AGI will be achieved. The implementation of the idea passes through different phases, from implants to the brain, through uploading software in the brain, to the emulation of the whole brain in the software. There are a number of projects following these phases, so, the information is not too „new”. The question is what this project has to do with manufacturing. The answer is relatively simple. There are the first experiments (already a few years ago) for robot control by brain signals, see e.g. (Robohub, n.d.), Figure 8. (the project is financed by Boeing and the National Science Foundation). The future is of course, controlling the whole production system by an artificial brain.

Figure 8. The feedback system enables human operators to correct the robot's choice in real-time. After (Robohub, n.d.)

The second project to refer to is *Manufacturing Singularity*. The manufacturing singularity is defined in (Putnik G. D, et al, 2020). It is defined as the point beyond which the production, including the strategy, planning, execution, etc., will be decided autonomously by the production system without any intervention of humans. This concept is defined in the spirit of AGI/ASI in general, and the question is if it is possible at all without achieving the singularity in general. The authors of this paper think that it is impossible. However, although thought as impossible, the usefulness of the concept is that it could serve as a reference value, to measure advances in autonomy, i.e. applications of AI/ML, in production systems.

6. Conclusions

The paper presents a brief overview of just some aspects of AI/ML applications in manufacturing. It is relatively easy to recognize that AI/ML applications are already „omnipresent" in manufacturing. However, the large majority of papers refer, at the moment, the „single-loop" learning models, which could be understood as just a first phase. In the second phase, it is obvious, that manufacturing, as other areas, has to face more advanced applications of AI/ML, especially towards AGI/ASI, independently of how realistic are AGI/ASI. Additional features of the future developments of AI/ML in manufacturing will surely imply social sciences, referring to the job issues, standards, security, ethics, and similar.

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