Artificial Intelligence and Cyber-Physical Systems

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Modern society is living in an age of paradigm changes. In part, these changes have been driven by new technologies, which provide high performance computing capabilities that enable the creation of complex Artificial Intelligence systems. Those developments are allowing the emergence of new Cyber Systems where the continuously generated data is utilized to build Artificial Intelligence models used to perform specialized tasks within the system. While, on one hand, the isolated application of the cyber systems is becoming widespread, on the other hand, their synchronical integration with other cyber systems to build a concise and cognitive structure that can interact deeply and autonomously with a physical system is still a completely open question, only addressed in some works from a philosophical point of view. From this standpoint, the AI can play an enabling role to allow the existence of these cognitive CPSs.

Keywords: artificial intelligence ; cyber-physical systems ; industry 4.0 ; digital twins ; chemical industry ; methane purification

1. Introduction

Technological advancements lead to several paradigm shifts in modern society. These advancements led to extremely fast computing capabilities, near-instant exchange of information at a global level, massive data generation, cloud data storage systems, etc. They also led to the emergence of novel cyber systems in which systematically generated data pipelines are used to perform specialized tasks [1][2][3][4]. For example, some countries employ artificial intelligence (AI) models to make use of video security imaging on the streets to identify criminals or potential crimes [5][6]. Furthermore, autonomous AI systems are used in healthcare [7], providing the identification of diseases in record time, such as the diagnosis of COVID-19. There are also several applications used in the chemical industry [8][9]. These new advancements are still very recent and have a high potential for creating critical changes in human society.

These new technologies are positioning the industry in a globalized context of intense renovation, where the system's performance is affected not only by their isolated operation but also by consumer demands, environmental, social, political, and worldwide financial situation. In this scenario, it becomes necessary to have an industry able to quickly respond, adapt and reconfigure itself while constantly optimizing and controlling its processes. Those demands are starting to exceed the human capacity to efficiently cope and swiftly answer to all these situations simultaneously.

In this context, the current advances in distributed computing, communications, and embedded systems have been presented as an opportunity to propose a new kind of distributed, large-scale, cooperative, and flexible automation systems, referred to as cyber-physical systems (CPS). A CPS is usually defined as a system composed of a physical process integrated into a network and computing system [10][11][12][13].

2. Cyber-Physical Systems Enabled by Artificial Intelligence

The focus of this work is to present and review the potential of AI application in an upper level of cyber-physical systems, enabling cognition to the system. On the lower level, within the system, AI can be an essential component within CPSs, for example, to perform faulty detection or real-time prediction of the system behavior [8][14][15][16]; to be used as a prediction model in control system architectures [17][18][19]; to perform process optimization [20][21][22]. This topic has been explored in the literature, as aforementioned. However, as the systems evolve, they become more and more complex. Nowadays, automatized systems tend to be composed of several components that should work harmonically in synchronicity. This requires refined tools at the decision level and at the operating management, which is a bottleneck in enabling large-scale CPS. Thus, AI is a crucial technology in enabling large-scale CPSs, making a bridge between the CPSs and providing them with real-time autonomous guidance.

AI can provide an essential ability for the system: cognition, which allows the modelling, representation and learning of complex behaviors and interactions between the system components and the system data. This can be achieved through the supervised or unsupervised training of AI models to perform these specific tasks. Moreover, AI models are able to continuously learn from the system, conferring an adaptive ability to the CPS. As such, there is an increasing demand for research on the development and integration of large-scale AI networks. It is important to note that these comments refer to the application of AI in an upper level of CPSs to perform human tasks.

Therefore, through AI it might be possible to achieve a capacity where the chemical unit can vertically integrate several levels of management on itself, communicating with the CPSs structures and performing the management task with autonomy. As indicated by [23] the idea of systems that can operate themselves with reduced human assistance has become popular in the last years due to the recent development in the automotive industry, with self-driving transporting systems. This concept is based on a robust autonomous controllability and autonomous cordiality whose demands are modularity, discreteness, functional equality, data sharing, situation consciousness and self-management. Most likely due to a lack of technology, the idea was not thoroughly developed in the literature and no other author after Koshijima et al. (1997) [24] has mentioned it since then.

An enabling step towards the concept of large-scale CPS coordinated by AI is provided by the Internet of Things (IoT) [25]. An industrial IoT network already provides an extensive network of interrelated computing devices where information is exchanged constantly and made available in real-time. Therefore, the IoT can provide the necessary social environment for the AI models to exchange experiences and information and manage the system under their coordination. Radanliev et al. (2020) [25] provided a comprehensive review of the application of AI within cyber-physical systems.

Furthermore, the identification of AI for dynamic systems is still an open issue. Dynamic AI is one of the most important representations for chemical engineering dynamic systems, which are often highly nonlinear, have high settling times and need frequent intervention considering its future states. The most suitable approach in this situation is the recurrent neural networks (RNN). Among the RNN techniques, the deep neural networks (DNN) are highlighted by their successful application to address problems of several fields. However, there is a lack of new studies in the process engineering field in order to make use of the DNNs potential to solve a series of issues from the field [26]. Deep learning has not yet found many applications in the field of chemical engineering processes. Even though the AI/deep neural networks (DNN) field is currently in continuous growth, its capability to address problems concerning system dynamics is still under development [26][27][28][29]. In addition, techniques from distributed AI are also an enabling technology for self-managing, cooperation, and virtualization abilities desired for the development of large-scale cognitive CPSs.

3. Control, Optimization, Artificial Intelligence and Cyber-Physical Systems

In the chemical industry, process control and optimization are fundamental issues that always need to be addressed. Without them, even in their most rudimentary version of manual control and visual inspection, a process cannot operate. The control system and optimization literature applied to the chemical industry is robust, where it is possible to find several developments of these topics through time. It is not the goal of this work to perform a revision of these topics; however, as they play a fundamental role in the chemical industry, they should be addressed in any further development made in this field. Therefore, they are here presented as building blocks of the CPSs here envisioned.

In an Industry 4.0 environment, it is essential that a system be able to adapt to changes as quickly as possible, ensuring the best possible scenario in each different set of circumstances. To accomplish this, advanced control and optimization strategies must be designed in order to meet a balance between precise forecasting and representability of a complex process [30][31].

Due to the complex and dynamic nature of CPSs, conventional process control tools such as PID (proportional–integral–derivative controllers) are not up to the task of meeting their demands. Thus, more advanced control strategies must be developed. Model predictive control (MPC) is considered the standard method for application in complex industrial systems [32]. In particular, according to several papers [33][34][35][36][37][38] nonlinear model predictive control strategies (NMPC) are known to perform better than linear MPC architectures.

However, there are several problems that prevent the practical implementation of NMPC techniques, such as the lack of strategies for a systematic tuning of the control parameters and restrictive conditions to guarantee stability and feasibility of the closed loop system. Moreover, the implementation of these methods requires high computational effort [30]. Thus, it is expected that research efforts will be focused on developing NMPC strategies to overcome the aforementioned challenges. These strategies should be able to guarantee closed-loop stability, with NMPC control laws that contemplate adaptive and active-learning formulations, yielding data-driven schemes for NMPC strategies.

Optimization of complex processes is, accordingly, a very complex task. An appropriate example of this can be observed in chemical processes due to the highly complex dynamics and interactions between the multiple process variables. Whereas the literature on off-line optimization of such systems is well established, based on detailed and rigorous models [31][23][39], real time optimization (RTO), which aims to dynamically provide the economically favorable and environment-friendly operating conditions, is still relatively unexplored. The main reason for this is the complexity of the optimization problem resulting from the use of stiff differential-algebraic system of equations (DAE)-based models. Substantial research efforts need to be invested in the use of RTO for on-line optimization strategies that are faster than DAE based models. In particular, RTO strategies based on DNN-type surrogate models are of particular interest to this topic. Deep Reinforcement learning [40] can also be used at this level to leverage the big data provided by CPSs. Deep reinforcement learning are strategies that present the potential to formulate a real-time optimization strategy that can learn gradually along the system lifetime. There are risks associated with implementing these optimization architectures, the main one being the increased computational burden that they entail. Similarly, to control strategies, striking a balance between computational burden and accurate representability of the CPS needs to be taken into consideration.

4. Digital Twins, Artificial Intelligence and Cyber-Physical Systems

The digitalization of a complete CPS in a virtual clone creates a virtual entity that is a mirror of both the cyber and physical systems, which can be a useful tool for system development, optimization, and monitoring. Allowing the existence of a virtual copy of the complete cyber-physical system can lead to several possibilities. This point involves the capacity to virtualize the cyber-physical system in a concise virtual environment, which can be used for real-time assessments of the physical environment, constantly learning from it, and providing reliable and precise information about the real scenario.

This process is called the twinning process or the building of a digital twin. The idea was originally proposed by Michael Grieves and John Vickers from NASA [41], which was, throughout the last decade, one of the first organizations to make use of the concept of digital twins, applying it to space exploration missions. A review of the literature shows that digital twins are claimed to be an essential technology for the new industrial revolution [42][43][44][45]. The number of publications focusing on digital twins [46] has been growing significantly since 2017, mostly originating from the areas of manufacturing and product life cycle assessment.

For instance, through the digital twin, it is possible to emulate and simulate in real-time the cyber-physical system behavior. The digital twin might be a key technology to provide an important tool to the system's robustness. Through the twin, the system can evaluate and predict the behavior of the physical system, while not compromising the operation of the physical system, drawing strategies to cope with the world dynamics. Furthermore, not only one twin can be built but several. Each twin might serve as a benchmark reference, with which the system will be able to check the CPS level and verify possible failures, malfunctions, or even digital threats. In summary, the digital twin can serve as a virtual and reliable laboratory for the system, through which it will be possible to identify new operating modes, plan and schedule maintenance, predict, diagnose and isolate faults, constantly improving the system efficiency. The twins can be coupled to the upper artificial intelligence models. In this way this upper AI level can make use of the twins' potential to perform autonomous evaluations with robust information about the system.

Digital twins play an important role in the advent of large-scale and complex cyber-physical cognitive systems. Based on this technology, it is possible to explore several scenarios with precision and reliability without the need for a physical system. It is a breakthrough technology because it frees users from important traditional constraints.

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