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Digital-Twins towards Cyber-Physical Systems: A Brief Survey

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Abstract:

Cyber-Physical Systems (CPS) are integrations of computation and physical processes. Physical processes are monitored and controlled by embedded computers and networks, which frequently have feedback loops where physical processes affect computations and vice versa. To ease the analysis of a system, the costly physical plants can be replaced by high-fidelity virtual models that provide a framework for Digital-Twins (DT). This paper aims to briefly review the state-of-the-art and recent developments in DT and CPS. Three main components in CPS, including communication, control, and computation, are reviewed. Besides, the main tools and methodologies required for implementing practical DT are discussed by following the main applications of DT in the fourth industrial revolution through aspects of smart manufacturing, sixth wireless generation (6G), health, production, energy, and so on. Finally, the main limitations and ideas for future remarks are talked about followed by a short guideline for real-world application of DT towards CPS.

Keywords: *Digital Twins, Cyber-Physical Systems, Control, Communication, Computation, 5G, Artificial Intelligence, Machine Learning, Computational Intelligence.*

1. Introduction

The first third industrial revolution, often known as the digital revolution, began in the late 1900s and was marked by the widespread use of electronics and computers, the advent of the internet, and the discovery of nuclear energy. Cyber-physical integration, which is rapidly being adopted by manufacturers, is a necessary foundation for smart production. It's a data-driven and model-driven system. Manufacturing is a form of cyber-physical integration that businesses are increasingly adopting. It's a data- and model-based system modeling approach that prioritizes simulation synchronization between the real and virtual worlds. CPS is a key enabler method that focuses on synchronizing the physical and cyber worlds in simulation [1]. CPS is a type of computing system that integrates physical items or systems with integrated computational and data storage capabilities. CPS is an important enabling technology in the field of systems intelligence [2].

The most important notion in cyber-physical integration is the DT. The major enablers of smart manufacturing are CPS and DT technologies. CPS's main goal is to create bi-directional interaction channels between the physical and cyber worlds, as well as to establish an IoT in the physical world to connect various sensors, actuators, and controllers with products and equipment for real-time data perception, transmission, processing, feedback, and service [3]. As the key technology of CPS, DT provides a clear and feasible way to realize the functions of CPS. The CPS model, in general, is used to model complicated physical plants or costly high-fidelity virtual models that have recently gotten a lot of attention because of their great potential in developing the next generation of smart systems that combine cyber technology into physical processes. There is currently no systematic and complete investigation of the connections and relationships between these two concepts [4]. The integration and collaboration of three terms including Computing, Communication, and Control are known as "3C" [5], [6], CPS provides sensing, real-time optimization, information feedback, dynamic control, and other services, see Fig.1 [7]. In this study, the state of the art and recent developments in CPS and DT are reviewed.

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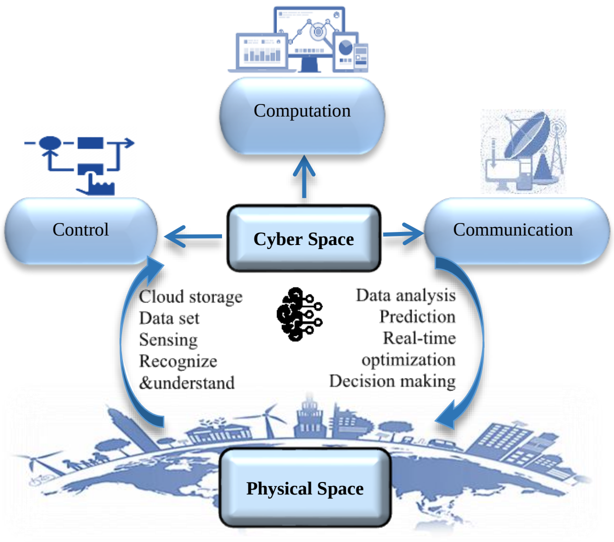

Fig.1 Representation of CPS [7].

This paper is organized as follows: Section 2 provides explanations of the CPS, the interconnection of CPS and DT, and the common principles of communication, control, and computation. Section 3 focuses on the recent practical applications of CPS and DT. The main limitations and relevant future remarks dealing with current real applications of CPS and DT are discussed in Section 4. Finally, this study was concluded in Section 5.

2. Digital Twins towards CPS

The basic idea behind DTs is to show features, processes, and systems in their entirety, both physically and functionally. The first step is to create high-fidelity virtual models that accurately recreate the geometry, physical properties, behaviors, and rules of the physical world. These virtual models are capable of simulating their spatiotemporal status, behaviors, functions, and more, in addition to being extremely consistent with the physical parts in terms of geometry and structure [8]–[10]. To put it another way, virtual models and physical entities have a similar appearance, like twins, and behave similarly, like a mirror image. Furthermore, models in the digital world can use the input to directly optimize operations and adapt physical processes [11]. CPS is characterized by DT, a novel simulation approach in Industry 4.0. (e.g., Big Data and Cloud computing as support systems to read big sets of data from the field, store and analyze them, and IoT to remain connected and extract data). This new simulation technique is also the foundation for leveraging manufacturing's pervasive connectivity to provide real-time synchronization with the field [12]–[14].

A DT generates high-fidelity virtual representations of physical objects in virtual space to mimic and offer feedback on their behavior in the real world. CPS and DT have gotten a lot of attention from scholars and practitioners in the industry as the chosen mode of integration [15], [16]. A DT reflects a bi-directional dynamic mapping process; it breaks the barriers in the product life cycle and provides a complete digital footprint of products. It creates a virtual twin of a physical entity (or system) to transparentize the physical entity's geometrical/physical/behavioral condition and allow real-time simulation optimization and control of the physical entity's performance (or system) [17], [18]. As a result, DT allows industries to predict and detect physical difficulties earlier and more precisely, improve manufacturing processes, and generate better products. The connections between CPS, DT, and 3C were mapped in Fig.2. CPS integrates 3C technologies to provide accurate control, distant partnership, and independent management for physical functions.

2.1 Communication

In wireless networks, CPS communication channels must be designed to be lossless and delay-free, as well as low-energy, shared, and rapid switching systems. A wireless (or cable) communication system platform with sufficient bandwidth is required in CPS to suit various enterprise requirements. Traditional single-network data collecting methods are unable to meet the complicated applications in CPS. CPS has merged ZigBee, Wi-Fi, Bluetooth, UWB (ultra-wideband), Ad-hoc networks, Mesh networks, mobile cellular communication networks, and the Internet, as well as other novel transmission systems. The most fundamental element of CPS is that sensors and actuators are required to interface with the physical world for data exchange, as they are in charge of sensing circumstances from physical machinery and the environment, as well as executing control directives. Any changes in the physical world (e.g., behavior, circumstances, or performance) induce changes in the cyber world, and vice versa, via sensors and actuators. As a result, sensors and actuators might be regarded CPS's essential components. The main aspects of communication required in CPS and DT environments are elaborated in [6], [19]–[21].

2.2 Control

In practical practice, several CPS systems have been constructed by decoupling the control system design. This allows for dependable, safe, collaborative, robust,

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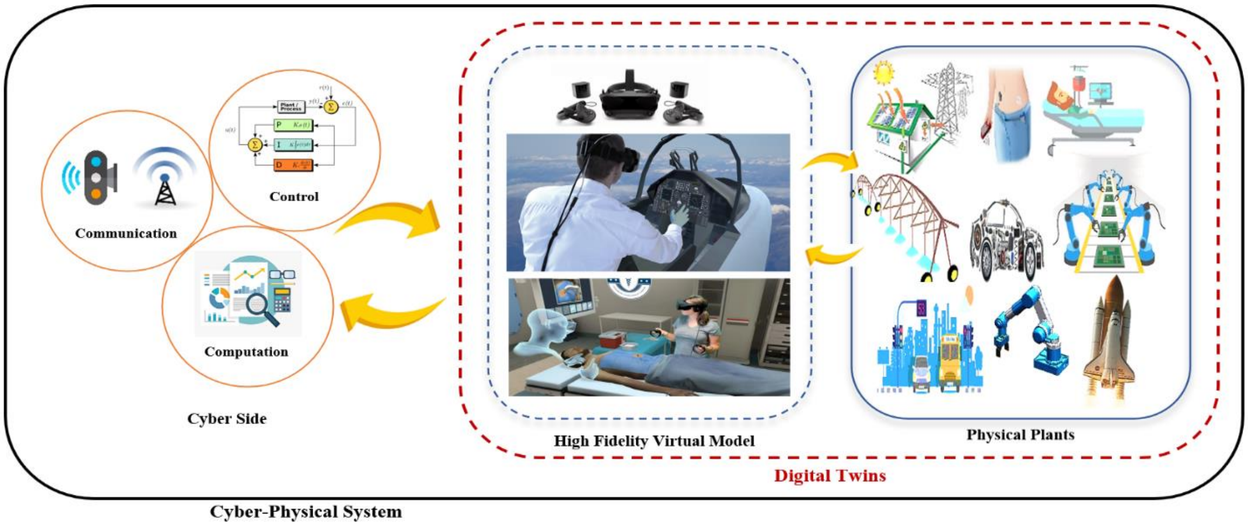

Fig.2 Digital-twins as a subsection of a cyber-physical system by the interconnection of physical plants and high-fidelity virtual model. Three main components in CPS include communication, computation, and control.

and efficient monitoring, and control of physical entities, as well as real-time interaction. Using precise calculations to regulate an unpredictably physical environment is a major problem. To keep the values of safety parameters within the established thresholds, intelligent controllers monitor and process physical process variables in real-time CPS control. Physical processes are generally managed using feedback loops in CPS embedded computers and networks, where physical processes affect computations and vice versa. Control commands are generated based on specified rules and the control semantic definition in the cyber world through data management, processing, and analysis. The results are given back to the actuators, which respond to changes by performing operations following the control directives. Real-time communication and data sharing are supported by the data and control bus. Control systems and their required specifications applied in CPS and DT have been studied properly in the literature, see [22]–[26].

2.3 Computation

In general, there are two types of computational techniques that have been applied in CPS and DT namely model-based methods and metamodel-based methods. Model-based methods have employed a direct physical model, simulation model, or mathematical expressions related to the physical model [7], [27]. Common model-based methods to solve and handle computational aspects for control systems in CPS and DT are genetic algorithms (GAs), and other well-known metaheuristics such as Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), Ant-Colony Optimization (ACO), and Evolutionary Programming (EP) [28]–[34]. However, applying physical models, simulation models, or dynamic mathematical expressions directly in the search process can increase computational complexity and computational cost. Investigating less computationally expensive (i.e. less number of iterations or function evaluations) methods have also become a main challenging topic in the practice of CPS and DT [35], [36]. Researchers have developed data-driven-based learning approaches known as metamodels to solve such computational challenges, see [37]–[39].

2.4 DT's Requirements (Tools and Methodologies)

Possibly, designing and implementing a practical DT model in CPS environments required employing some main tools and methodologies which are essential in DT real-world applications. Such main requirements, not all can be as follows:

- **Artificial Intelligence (AI)**

AI, robotics, the Internet of Things (IoT), genetic engineering, quantum computing, cloud computing (CC), big data analytics (BDA), and more are all part of the 4th Industrial Revolution (4IR) [40] are some such the state-of-the-art technologies that have greatly stimulated the development of DT. A current White House study on AI [41] emphasizes the importance of AI and the need for a defined roadmap and deliberate investment in this field. This digital transformation is being hailed as being heavily reliant on AI. Even with the disruptive Production 4.0 technologies currently available, the bulk of connected manufacturing devices still requires human intervention for decision-making processes like initiation, management, monitoring, and feedback. These physically interconnected entities can generate exponentially more value if intelligence is added to them. The creation of a smart factory, which would require little to no human intervention, is made easier by AI [42].

- **Machine Learning (ML)**

A significant part of DT is anticipated for the AI subfield of ML. ML can broadly be divided into three categories: supervised, unsupervised, and reinforcement learning [43]. The majority of the frequently employed supervised algorithms include Linear Regression, Logistic Regression, Support Vector Machine [44], Decision Trees, Random Forest, and Artificial Neural Networks [45]–[47]. Such unsupervised algorithms are namely self-organized maps (SOM) [48] and clustering analysis [49] (k-mean, t-SNE [50]). Although supervised and unsupervised learning machine learning algorithms have been the most often used algorithms in practical applications, they are not very useful when there is not enough data. Even though it is still in its infancy, Reinforcement Learning [136] has the potential to be helpful in this data-limited circumstance. It may be a crucial enabler for intelligent decision-making systems in Industry 4.0-related technologies [51].

- **Virtual reality (VR)**

By combining a series of different technologies, including a head-mounted display with head-tracking systems, headphones for sound/music and noise-canceling headphones, as well as manipulation navigation devices, VR technology provides a multisensory, and three-dimensional (3D) environment that enables users to become fully immersed in a simulated world [52]. VR and DT are important technologies for designing, simulating, and optimizing CPS, as well as interacting with them remotely or collaboratively, in the context of Industry 4.0 [53]. VR may be regarded as one of the important technologies that have the potential to expand viewpoints across numerous industries [54]. Some review papers discuss the most recent developments in the application of VR in engineering and design [55]–[59], medical [60]–[64], and education [65]–[68]. A VR interface that is fully immersive enables improved perception and comprehension of the DT. With this suggested method, design errors may be found during virtual commissioning before the actual implementation, avoiding expensive and sometimes unmanageable repercussions. The DT may also be utilized for operator training after deployment, due to the virtual reality interface, for real-time process monitoring, realizing the real-time data from sensors, and for testing upcoming modifications [69].

- **Fifth Wireless Generation (5G)**

Any DT that functions reliably will need data from several components to reach its intended destination on time. For instance, during robotic surgery, a surgeon's actions in a virtual operating room should instantly take place in reality [70]. The DT communications mainly refer to information exchange between a physical object and a virtual twin carried out via wireless communication technologies. The physical object exchanges its data in real-time and receives feedback from the virtual twin. Legacy networks have a huge cell size; however, in next-generation networks, the cell size is dramatically reduced, which creates a major challenge for telecommunication network operators to scrupulously plan their complex networks. Networks of the 5G and beyond necessitate the massive deployment of base stations [71]. Wide-area network wireless communication technology, namely 5G cellular communications, is the major form of technology used here for communication [72]. One of the barriers to achieving DT's potential is the necessity for high throughput (100 Gbs), dependable (99.999 percent), and ubiquitous communication, which calls for beyond-5G technology. Therefore, 6G might be seen as a catalyst for the widespread deployment of DT [73].

- **Computational intelligence (CI)**

Since digital twins frequently employ intricate mathematical models, it is difficult to apply efficient optimization techniques, such as non-linear multi-responses constrained optimization [74]–[77], real-time intelligent control [7], [78]–[81], robust uncertainty management [39], [82], due to their high processing requirements. Most simulations used in real-world DT require a lot of computational costs to assess the various unknown model functions [83]. For such computer-aided designs or simulation-based optimization using computer experiments with high computational cost (i.e., a high number of function evaluations to solve the problem), traditional model-based optimization methods may perform poorly or may even fail to obtain a satisfactory solution within the allocated

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computational budget. To avoid this, researchers turn to CI methods such as agent-based algorithms [84], fuzzy logic [85], [86], artificial neural networks [87], and metamodeling techniques [27], [38], [88], [89]. The application of metamodels (also called surrogates) is crucial for real-world optimization and analysis applicable in practical DT implementations [90], [91]. Metamodel-based methods can 'learn' the problem behaviors and approximate the function values. A metamodel by mathematical expression $\hat{Y} = f\widehat{(X,Z)}$ can replace with true functional relationship $Y = f(X,Z)$, where X and Z denotes respectively design and noise (uncertain) parameters in simulation model, see Fig.3. These approximation models can speed up the function evaluation and the estimation of the function value with acceptable accuracy [92], [93].

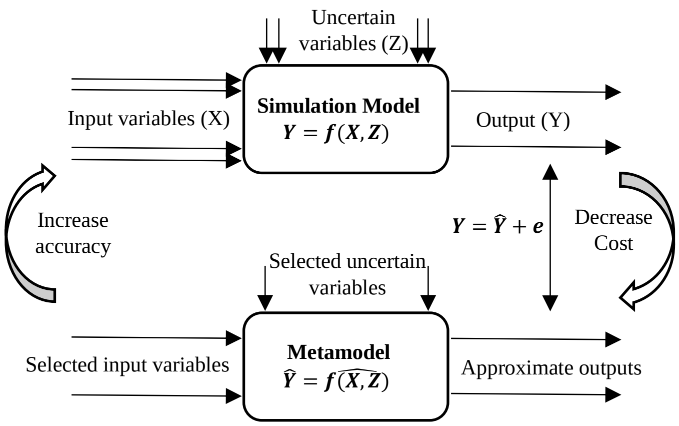

Fig.3 A Schematic viewpoint of metamodeling technique [27].

3. Practical Applications

CPS has had a lot of growth in recent years, and it's now being used in a lot of various applications. In the following, we briefly review some of the practical applications of DT and CPS in a few real-world disciplines such as healthcare, manufacturing and production, energy management, and so on.

- **Industrial and smart manufacturing**

The smart factory was first researched with the introduction of the Internet of Things in production, and it later became a significant component of Industry 4.0. With the introduction of cloud computing (broadly, the Internet of Services, IoS), social networking (broadly, the Internet of People, IoP), and big data (broadly, the Internet of Content and Knowledge, IoCK), other related models such as cloud manufacturing, social manufacturing, and proactive manufacturing are also emerging [4]. To promote the notion of Industry 4.0, a DT project was conducted in [11] that focused on continuous optimization of manufacturing processes, proactive maintenance, and continuous analysis of process data. The authors in [7] have developed the CPS framework in real-time optimization and robust tuning of Proportional-Integrative and Derivative (PID) control systems considering the effects of uncertainty and noise in different fields of smart industries such as robotic and automation as shown in Fig.4. Ref.[94] has proposed an industrial Internet-of-Things hub, consisting of a customized access module, access hub, and local service pool, to achieve smart interconnection in dealing with heterogeneous equipment, quick configuration and implementation, and online service generation toward smart manufacturing using a CPS. Ref.[95] has presented a natural human-machine interface that brings human decision-making capabilities inside the cybernetic control loop of a smart manufacturing assembly system, allowing to control, coordination, and cooperation with an industrial robot during task execution, to reduce the technological barriers required for the interaction of tight networking capabilities and efficient interfaces for human interaction.

- **Towards 6G Wireless Systems**

Towards 6G implementation, requires innovative paradigms including integration of the features of AI in particular ML [96], [97], Augmented Reality (AR)/ VR [98], [99], and connected three components of communication, control, and computation as three main components recognized to "3C" in CPS, a necessary foundation for 4th Industrial Revolution (4IR) [15], [40]), which has not been fully addressed in 5G, given the expanding capability of these approaches in communication [72], [100], [101] to enable the smart applications such as smart healthcare, smart cities, smart manufacturing plants, smart airports, and so on. To design a wireless system by following the aforementioned paradigms, features, and components to enable smart applications, a comprehensive digital representation of the physical world can be created and maintained through the DT framework [73], [102], [103]. A DT is a virtual representation of an asset (e.g., 6G wireless system) that provides a historical record of the asset's previous states as well as real-time data on the asset's current state. However, despite a few studies, the design of DT for an upcoming generation of a wireless system is still a work in progress, and several main challenges have remained to achieving the benefits of a DT-based wireless system, particularly for the interconnection of intelligent features (e.g., AI, ML, and

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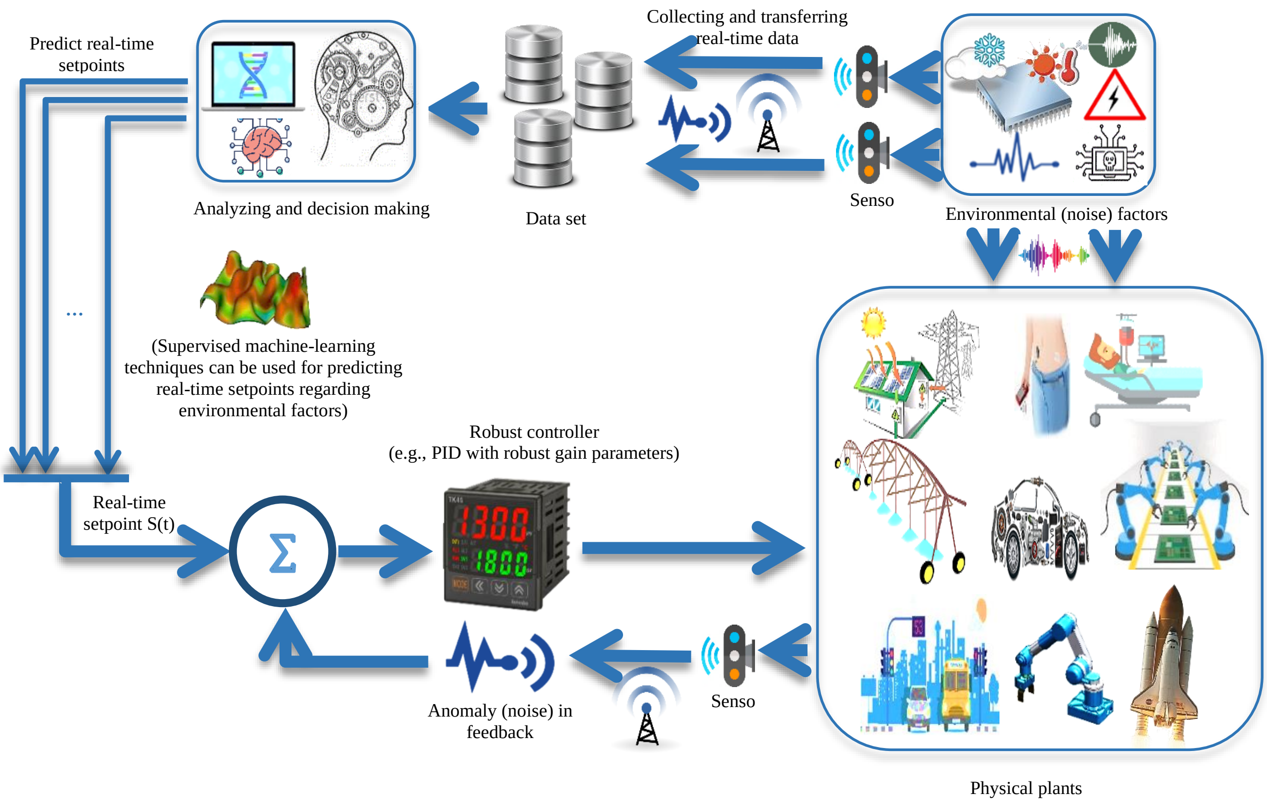

Fig.4 A CPS framework for robust closed-loop control system considering uncertainty and noise factors. Approximation learning methods can be used to predict the real-time setpoint [7].

VR) to smart applications (e.g., smart healthcare, smart manufacturing, smart cities, etc).

- **Healthcare**

Medical cyber-physical systems (MCPS) are a network of medical devices that are vital to healthcare. These systems are gradually being implemented in hospitals to provide consistently high-quality care. In addition to interoperability, security and privacy, and high assurance in the system software, the MCPS design faces some obstacles. Ref. [104] discusses networked medical device systems, including the concept of social networking and its security, as well as the concept of wireless sensor networks (WSNs). To capture the effects of interactions between computer units and the physical environment of medical CPS such as infusion pumps, the authors in [105] presented a new technique based on a set of interdependent partial differential equations associated with specialized modes. The study in [106] used a CPS approach for the artificial pancreas, which included blood glucose (or blood sugar) level sensors to control an algorithm that determined the insulin injection dose, an insulin infusion pump, and delivery system, and a communication platform that connected to the patient's cellphone and sent real-time alerts to medical experts. In [107], the authors propose a human-centered cyber-physical systematic approach for post-stroke monitoring that includes wearable inertial and physiological sensors, as well as novel ML algorithms for analyzing human behavior and physiological signals in the context of health care for patients with cerebrovascular diseases like stroke. ML also is applied in [45] for real-time health prediction of induction motors utilized in a petrochemical plant through the application of intelligent sensors.

- **Vehicle**

Advanced diagnosis and prognosis technologies are needed to quickly detect and isolate faults in network-embedded automotive systems so that proactive corrective maintenance actions can be taken to avoid failures and improve vehicle availability, according to an automotive CPS approach proposed in [108]. A new model for quantitative capability maturity evaluation of smart manufacturing workshops has been developed by Ref.[109], which provides directive guidelines and a roadmap for the transformation of automotive manufacturing companies. The authors of [110] describe various methodologies for approaching cooperative vehicle safety design and propose a systematic CPS approach to cooperative vehicle safety design. They offered a top-down approach to system design, establishing system metrics such as approximate measures of awareness, and describing component models, and their relationships. Ref.[111] addresses a new driver-centric service delivery problem from a cross-disciplinary resource allocation standpoint, proposing several efficient heuristics to address several issues, including wireless transmission failure and the distributed implementation of multi-sender systems, to maximize system-wide performance in terms of total utility income to drivers. Electric vehicles pose new challenges in CPS design when compared to combustion engine vehicles. The study in [112] provides an overview of several of these challenges as well as preliminary and probable solutions for the design of electric powertrains and electrical/electronic architecture for electric vehicles.

- **Renewable energy**

The design and development of a testbed to evaluate various smart-grid-based control technologies were described in [113] using controller hardware-in-the-loop real-time simulation to examine various "intelligent" and distributed control algorithms by describing the impacts of various interactions such as communication timings, available computational resources, and distribution and decentralization of higher-level control on a microgrid's operations. The study in [114] obtained a yearlong, detailed measurement of the real-time blend of supplies on the primary California grid dispatched to meet current demand and then scale the solar and wind assets, while preserving uncontrollable weather effects, to a level of penetration associated with California's 2050 GHG targets by addressing CPS challenges in today's electric grids. The impact of demand shaping, storage, and agility on the rebuilt supply portfolio was also examined, as well as the duration curves and ramping that resulted, as well as the distributed control and management regime. Ref. [115] proposed a novel DT-based day-ahead scheduling method using a deep neural network approach to make statistical cost-saving scheduling by learning from both historical forecasting errors and day-ahead forecasts by addressing multiple uncertainty sources and the complicated surrounding environment in the practice of an integrated energy system. The authors of [116] used a deep-learning approach to consider a DT of a photovoltaic solar farm by appropriately evaluating and processing sensor-based time series.

- **Safety and Security**

Information security, in essence, is concerned with preventing information assets, such as intellectual property and sensitive personal information, from falling into the hands of individuals seeking to commit fraud or other criminal actions. Those responsible for the safety of software-intensive systems, on the other hand, are focused on ensuring that a system malfunction or breakdown does not result in harm to humans or the environment. The study in [117] analyzed the totality of hazards across a broad range of CPS in the public and private sectors and pointed to areas that must be subjected to much greater examination to mitigate increased risks by merging security-critical information systems and safety-critical control systems. The authors of [118] investigated three essential qualities that CPS operation must ensure: 1) safety: avoidance of dangers; 2) security: assurance of information integrity, authenticity, and secrecy; and 3) sustainability: long-term operation of CPS using renewable energy sources. Cyber-Physical-Security is a novel term that has emerged from the literature on the integration of CPS and security systems. One of the key features of CPS that has been explored in [119] is health care security in pervasive health monitoring systems. A similar issue was addressed in [120], which proposed a methodology for analyzing the safety features of closed-loop medical device systems in clinical use cases to improve patient safety.

- **Aerospace**

Global travel has become a fact of daily life because of a century of revolutionary growth in aviation. In the physical world, aircraft and air transport overcame several significant challenges and hostilities. This vision is streamlined by the tight convergence of the internet and the physical world. In [121], a unique CPS paradigm was presented to explain the cyber layer and cyber-physical interactions in aviation, explore their impacts and offer valuable research topics to address current CPS challenges and solutions for aircraft, aviation users, airports, and air traffic management. A neural model for digital air traffic control has been developed using the concept of socio-cyber-physical self-organization of distributed organizational and technical systems, whose components are connected to 4G and 5G generation wireless networks for controlling the security of the airport airspace with the concept of DT, according to

Ref.[122]. The study in [123] developed a DT technology by merging a convolutional neural network algorithm with an unmanned aerial vehicle autonomous network to investigate the airspace structure and safety performance of unmanned aerial vehicle systems based on spatial DT.

- **Other applications**

Many real-world engineering design challenges have been studied in the literature, and the practical use of DT and CPS is not restricted to the aforementioned applications. The authors of [124] used DT technology in the construction of an interactive lighting system for a museum. Ref.[125] proposes a CPS framework for aggregating and disseminating traffic flow-related information by combining resources and capabilities at the nexus between the cyber and physical worlds. Ref.[126] proposes a process for developing a flexible and semantic middleware for cyber-physical systems by focusing on the challenge of controllability in a heterogeneous wireless infrastructure of a smart home environment with a semantic and model-based approach to react to the rapidly changing environment and thus assist the user in seamlessly integrating their devices, such as new sensors. The interdisciplinary challenge of combining semiautonomous robotics, wireless body area networks, embedded system design, and intent inference algorithm development has been considered human-in-the-loop CPS by Refs.[127], [128]. It offers an exciting class of applications both for restoring or augmenting human interaction with the physical world faced with the interdisciplinary challenge of combining semiautonomous robotics, wireless body area networks, embedded system design, and intent inference algorithm development. Studies by [129]–[133] might be consulted for more real-world uses of DT and CPS.

4. Limitations and Future Remarks

The CPS is a multidimensional and complex system that integrates the cyber and physical worlds. The fundamental problem addressed in CPS is integrating physical processes with computer systems, as the computational cyber component continuously perceives the condition of the physical system and applies decisions and actions for its control [134]. The relationship between physical and information components is complicated and dynamic in CPS, which has a high number of heterogeneous components. As a result, one of CPS's primary challenges is detecting the communication efficiency of heterogeneous components [6]. In front of the limit, we only have so much time and space [135]. Limited energy supply allows CPSs to work for a limited amount of time, limited processing power determines the minimum required time for a specific computation, and limitations on communication, sensing, and actuation limit the rate at which CPSs can detect or alter their surroundings. Kinematic restrictions such as limited maneuverability, limited communication range, and the physical size of individual CPSs that can prevent them from entering constrained locations are examples of spatial constraints [136]. Despite the rising need for smart healthcare systems, given that healthcare is one of the largest costs for a variety of governments throughout the world, there is no unified theory that supports the relevant design and optimization of efficient and robust cyber-physical systems [106].

The authors in [137] have mentioned five challenges that should be addressed to achieve a reliable and resilient CPS that includes three features stability, security, and systematicness. These five challenges are

i) *Dependability and Adaptability:* Any CPS should have a high level of dependability. The framework intelligent physical world [138], for example, aids in the addition of adaptive behavior to the CPS. Adaptability leads to increased dependability. There are three domain characteristics when looking at the physical world as a black box system: programmability, observability, and computability. Dependability can be accomplished using these properties.

ii) *Consistency:* Each component in the CPS can be accounted for in a base architecture [139], and connectors allow for every method of communication and physical connection between pieces in the base architecture.

iii) *Reliability:* Computer programs are virtually 100% reliable in the sense that they execute the same set of commands in the same order every time they are run. Physical systems, on the other hand, rely not just on function but also on timing, and computer programs might be flawed in this regard. This discrepancy leads to a lot of ambiguity and unreliability, which is an issue for CPS [140]. Some AI or ML algorithms can be utilized to predict the next-time system state to make CPS behavior predictable. To explain the CPS time evolution dynamics, for example, we may use an approximation model [7].

iv) *Cyber-physical mismatch:* Interaction and coordination between the physical and cyber parts of a system are critical aspects of a CPS. One of the most prominent properties of the physical world is its dynamics, or how the state of the system changes over time.

v) *Cyber-physical coupling security:* A CPS should be able to withstand natural disasters as well as malevolent attacks. We'll go over how to design a resilient CPS by using a suitable control model and corresponding security schemes. From a monitoring and control safety perspective, the physical systems in CPS are vulnerable to cyber security problems.

5. Conclusion

DT is an improvement in digitalization. It is being used more and more often in fields including smart manufacturing, building management, smart cities, healthcare, and a wide range of other fields. Many businesses and scholars are not familiar with the primary technologies and tools of DT since it is a complicated system incorporating several technical disciplines. This paper provides a short review of CPS, DT, the main required tools and methodologies for implementing a practical DT, and the practical applications of DT and CPS in the 4th industrial generation including smart manufacturing, production, healthcare, energy, and so on. The interconnection of CPS and DT with three components of control, computation, and communication are explained. Additionally, the main limitations of the real-world application of CPS and DT are discussed at the end which can be a short-term guideline for researchers in future remarks.

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