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Integration of Industry 4.0 Related Technologies in Construction Industry: A Framework of Cyber-Physical System

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ABSTRACT The Fourth Industrial Revolution (Industry 4.0) is reshaping the construction industry and bringing it into an intelligent construction era. Emerging technologies, such as the Building Information Modelling, Internet of Things, big data, cloud computing, and artificial intelligence, have penetrated into all stages of the building life cycle and play a significant role. However, the major issue of intelligent construction is integrating multiple technologies to create more potential opportunities rather than their fragmented application. Considering the various special characteristics of the construction industry and the high heterogeneity of these technologies, their integration in the construction industry is challenging and requires in-depth investigations. This paper summarizes the Industry 4.0–related technologies involved in the construction industry based on an analysis of the characteristics of the industry. Further, this study presents a framework of a cyber–physical system to integrate these technologies and improve the overall capabilities of construction organization and management. A case study of the Xiong'an citizen service center is introduced to verify the technological feasibility and preliminary implementation effect of the proposed framework. As forward-looking research, the significance of this paper may also to inspire more efforts in this field.

INDEX TERMS Construction industry, industry 4.0, cyber-physical system.

I. INTRODUCTION

Construction is an ancient industry accompanied by hard manual labor and largescale equipment. From the perspective of industrialization, the construction industry is a unique manufacturing industry in which the products (i.e., buildings or structures) are assembled through a series of discontinuous processes. However, the construction process is complicated, which has led to its slow industrial evolution. In particular, in some developing countries, the construction industry still follows traditional labor-intensive industry practices, with high energy consumption, environmental pollution, and safety risks and low productivity in project delivery [1]. However, this may be changing with the advent of the Fourth Industrial Revolution (Industry 4.0). The visionary ideas of Industry 4.0 will encourage the development of the construction industry [2]. Emerging technologies, such as the Internet of Things, big data, cloud computing, and artificial intelligence, have been proven to effectively contribute to industrial intelligence, especially in the manufacturing industry [3]. In recent years, these technologies have gradually entered many fields of the construction industry [4]–[6] to support efficient design optimization, performance evaluation, resource management, risk monitoring, energy saving, emissions reduction, and project delivery. Despite these advances, intelligent processes in the construction industry are still in a nascent stage and lag behind other industrial sectors [7]. Presently, the innovative technologies are only partially adopted in specific fields, and there have been few macroscopic studies on their integration. A future issue is determining how to integrate multiple intelligent technologies to improve the overall capabilities of construction organization and management rather than their fragmented application.

With the deep integration of industrialization and informatization, a new ecosystem, namely the cyber–physical system (CPS), has emerged [8], which unprecedentedly entangles the network and physical worlds. This has initiated a new era of real-time communication and cooperation between value network participants, including devices, systems, organizations, and people [9]. According to the development trends of manufacturing, intelligent technologies have been important drivers for CPS deployment [10]. Meanwhile, CPS is also

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becoming a platform for the integrated application of intelligent technologies, which provides valuable inspiration for the construction industry.

However, to our best knowledge, there have been few studies on the CPS in the construction industry, especially considering the integration of multiple intelligent technologies. Correa [11] adopted the Petri Net as a cyber model for a construction process in the CPS, and two application scenarios of automatic assembly and traditional structural masonry were simulated. As a theoretical study, it did not illustrate how to apply the proposed CPS framework into a practical engineering environment, such as the deployment of cyber models and the realization of bi-directional coordination between cyber models and the physical construction. Akanmu *et al.* [12] discussed a radio frequency identification (RFID) technology enabled bi-directional coordination mechanism between virtual models and physical construction to improve the construction project delivery process, but they did not consider the management and utilization of the largescale data generated by the RFID, which is critical for project decision making. The purpose of this paper is to improve the over capabilities of construction organization and management by integrating Industry 4.0 related technologies into a unified CPS framework. We analyzed the research progress and gap through a systematic literature review, established a theoretical model of the proposed CPS framework, and verified the feasibility and implementation effect of the CPS framework through a case study.

The rest of this paper is organized as follows. The special characteristics of the construction industry that may hinder its intellectualization are discussed in Section II. The development status of Industry 4.0–related technologies in the construction industry and the potential integration opportunities for CPS implementation are summarized in Section III. In Section IV, a framework of the CPS integrated Industry 4.0–related technologies for the construction industry is proposed. In Section V, a case of the Xiong'an citizen service center is presented to verify the technical feasibility and implementation effect of the proposed CPS framework, and the potential benefits and challenges are further discussed in Section VI. Finally, conclusions are presented in Section VII.

II. ANALYSIS OF OBSTACLES TO INTELLIGENT CONSTRUCTION

To pave the way for intelligent processes in the construction industry, the factors that hinder the application of intelligent technologies are described based on the analysis of the basic characteristics of the construction industry.

A. UNIQUENESS OF PRODUCT

Unlike the standardized product processes of the manufacturing industry, each product in the construction industry is unique, and even buildings with the same design drawing also face different climatic and geological conditions. Therefore, there are no standard construction plans in the construction industry, and it is difficult to produce a bill of materials (BOM) like that in manufacturing [13]. The uniqueness of the product results in a temporary nature of construction teams (including owners, designers, contractors, subcontractors, and suppliers), and the construction system is a one-off production system. To build an integrated intelligent system, it is better that every component is modular and reusable, although this is a challenge under the current technical conditions.

B. DISCRETENESS OF CONSTRUCTION PROCESS

Unlike the assembly line operation in the manufacturing industry, construction is a highly discrete process with an unstructured organization and non-linear workflow. Tasks are rarely connected in a consecutive chain. Instead, work between or within tasks is connected to other work through shared resources or relies on other ongoing work. Different tasks are often assigned to subcontractors with different informatization levels, and it is difficult for the project owners and general contractors to obtain accurate information from them. Incompatible information flows lead to inconsistencies in the understanding of the project between participants, and their coordination requires considerable time and resources, which is not conducive to the construction organization and management [14].

C. LIQUIDITY OF CONSTRUCTION RESOURCE

The construction resources generally include the labor force, construction equipment, and building materials, which must be constantly transferred during the construction progress. The execution of tasks often requires multiple participants at different locations to work together in a changing environment. Thus, the spatial-temporal conflicts, such as those in the workspace, working sequence, and moving path are very common, which creates higher requirements for the coordination between them.

D. COMPLEXITY AND HIGE UNCERTAINTY

In a dynamic construction progress, each factor is an independent variable, and interactions between multiple variables lead to complexity and high uncertainty. Existing construction management models (e.g., the work breakdown structure (WBS), critical path method (CPM), and earned value management (EVM)) and their implementation tools have been criticized as being deficient for handling the complexities of projects [15]. Although managers have formulated a detailed construction plan, the high uncertainty of a project often leads to frequent modifications of the plan during construction. However, there is no appropriate evaluation method for the revised plan, which leads to the frequent occurrence of delays, overruns, reworking, poor quality, and even engineering claims. To address the uncertainty, project managers usually leave enough redundancy when working out the plans, but this also results in a waste of resources [16].

E. HARSH CONSTRUCTION ENVIRONMENT WITH HIGH RISK

Compared to a pristine shop-floor in the manufacturing industry, construction sites are often accompanied by noise, dust, wastewater, and mud, and some underground projects even face with the risk of engineering geological disasters, such as collapse and water inrush. Such a harsh construction environment introduces great challenges for the data acquisition and network communication of intelligent systems as well as the reliability of precision equipment. Furthermore, workers in a harsh environment cannot always focus on what is happening around them, and the lack of real-time information often makes them unable to react in time when facing dangerous situations. This sense of insecurity further hinders their willingness to cooperate with mechanical equipment [17].

III. OVERVIEW OF INDUSTRY 4.0 RELATED TECHNOLOGY INTEGRATION IN CONSTRUCTION INDUSTRY

In this section, nine Industry 4.0–related technologies that have been applied to the construction industry are summarized, and their potential integration opportunities and challenges are reviewed.

A. BUILDING INFORMATION MODELING

Building information modeling (BIM) originated from computer-aided design (CAD) and has now evolved into an innovative technology that supports the whole life cycle of a construction project by providing a virtual model and relevant information about buildings. According to the definition of the National Institute of Building Science (NIBS) of the United States [18], BIM is the ''sharing of knowledge resources for information about a facility, forming a reliable basis for decisions during its life-cycle; BIM exists from the earliest conception to the demolition of a construction project.'' By incorporating geometric, topological, and metadata properties, BIM can offer a high accuracy representation of a project at the component level. An integrated 3-dimensional model was adopted to completely express the definition information of buildings, which ensures the uniqueness of the data in the life cycle of the buildings [19]. BIM has already introduced profound changes in the construction industry by providing a unified platform for all stakeholders to communicate and collaborate in an efficient way throughout the entire lifecycle of a project. The subject of BIM is currently a central topic for the improvement of the construction industry, and it is a core technology for supporting the idea of Industry 4.0 in the construction industry [7].

The BIM model not only reflects the designer's expectations, but also provides a virtual replica of the building under construction. The manufacturing industry has a similar concept called the ''digital twin,'' a virtual model of the physical product created in a digital way to simulate its behaviors in real-world environments [20]. The emergence of the digital twin has paved the way for cyber-physical integration. It serves as a bridge between the physical and cyber worlds [21] that will provide the construction industry with a new paradigm to carry out intelligent construction. In the context of Industry 4.0, integrating with other innovative technologies could enable BIM to create a digital twin to interact with the physical building, which will provide a new means for monitoring, simulating, and making decisions in engineering projects.

B. INTERNET OF THINGS

The Internet of Things (IoT) is a disruptive technology that brings physical objects into a cyber world [22] based on devices or technology such as sensors, actuators, RFID, video cameras, and laser scanners. It achieves the ubiquitous connection between things in accordance with the agreed communication protocol and then senses, recognizes, and controls the physical process. Different types of sensors are deployed on a construction site for the real-time monitoring of the actual construction process. The data collected by sensors will be transmitted by a gateway (e.g., Wi-Fi, ZigBee, or Bluetooth) to the internet [23] to support more efficient performance evaluation, resource optimization, risk monitoring, energy conservation, emission reductions, and project delivery. However, most current IoT solutions in the construction industry are isolated for specific applications but lack coordination over the entire construction process. Thus, it is important to integrate the multidisciplinary IoT data to support the comprehensive monitoring and decision-making of the project.

Taking advantage of the Internet of Things, the real-time data collected from a construction site drives BIM models to monitor the construction process. However, it is challenging to link heterogeneous data from the IoT into the BIM for a real-time visualization and operation [24]. A widely adopted method is to establish a mapping structure between the IoT data and BIM data in a relational database and then import and export the model data through the existing API of the BIM tools (e.g., Revit DB link). This method can easily link the model and sensor data without additional programming efforts. However, once the model changes, the mapping structure in the relational database must be manually reconstructed, so it is not suitable for complex BIM models. Some recent studies have focused on developing domain-specific database schemes to provide flexible data integration between the BIM and IoT, although this requires users to have more programming knowledge [25]. For instance, Solihin *et al.* [26] defined a new database scheme named BIMRL that transforms the BIM data into a relational database and extends the BIM data query capabilities into standardized SQL. Alves *et al.* [27] created a domain specific query language named BIMSL with a customized API. BIMSL can handle contextual data queries and component-related time-series data queries. The above-mentioned studies only considered the data integration between the IoT and BIM. A further discussion will be carried out in the context of big data in Section III.D.

C. CLOUD COMPUTING

Cloud computing is an emerging technology for transferring and storing data and perform calculations at third-party data centers, which can be used by communication devices, such as PCs and mobile devices. Cloud computing now has become an Internet computing paradigm with on-demand access provided to the shared pool of customizable resources [28]. Cloud computing provides three service modes [29]: (1) Infrastructure-as-a-Service (IaaS), which provides users with virtual computers and servers; (2) Platform-as-a-Service (PaaS), which provides users with services such as operating systems, databases, and programing languages; (3) Software-as-a-Service (SaaS), which allows users to access their applications through the Internet. In summary, the cloud provides virtualized services for scalable storage and computing, which is more reliable due to a reduced dependence on the physical infrastructure.

Cloud computing is widely used in the construction industry due to its support for BIM-based applications, which can overcome the BIM challenges by providing real-time access to the data pool and computing resources. Das *et al.* [30] presented a cloud-based BIM framework for integrating stakeholder's interactions. Redmond *et al.* [31] adopted the cloud for interoperability between the BIM and other applications. Combining MapReduce, WebGL 3D, and other technologies, Chen *et al.* [18] proposed a cloud-based framework for online viewing, storing, and analyzing massive BIM, which enables users to access to the Cloud-BIM via various types of devices connected to the internet anytime and anywhere. The combination of cloud computing and BIM will enable all participants in the construction industry to collaborate on a unified platform, change their original isolated and decentralized state, and promote the efficient integration of the construction industry chain.

The integration of the IoT with cloud computing is urgently needed in the construction industry, because the limited data processing capabilities of IoT devices and the harsh construction environment do not allow on-site data processing. By integrating with cloud technology, the IoT can benefit from nearly unlimited virtual computing resources to overcome its technological constraints and implement real-time, collaborative, and scalable applications. In this sense, IoT acts as an intermediate layer between physical things and virtual resources [32]. The elasticity of computing resources of cloud services can also meet or extend the needs of specific applications, enabling the integration of multiple intelligent technologies in the construction industry, solving the problem of process information opacity caused by the discrete construction industry. The storage and computing capabilities provided by the cloud service have acted as an enabler for industrial scenarios [33], not only for big data storage and analysis but also for high-performance intelligent computing.

D. BIG DATA

The emergence of big data is the result of advancements in information technologies. Its significance is not to manage massive amount of data, but rather to extract the values hidden in them. In general, big data can be defined by 4Vs characteristics: volume, velocity, variety, and value. For the construction industry, big data refers to the data generated from the life cycle of the building or structures, such as the phases of planning, design, tendering and bidding, construction, checking before acceptance, and operation management. These data come from multiple sources including the IoT (e.g., data streams from sensors or RFID readers) [32], information systems (e.g., BIM, project management system (PMS), and enterprise resource planning (ERP)), and the historical project documents [13], which are also characterized by the 4Vs.

The essence of systems integration is data fusion [5], which contributes to establishing the interoperability between them, e.g., linking the IoT data to BIM, and realizing data exchange between BIM and enterprise information systems, such as enterprise resource planning (ERP) and project management system (PMS) [13]. However, due to their heterogeneous nature, this work is challenging. The Industry Foundational Class (IFC) [34] is a de facto general data standard for the construction industry, and a commonly used scheme is to convert other data formats to IFC for integration with the BIM data. Extracting the values hidden in massive data is the significance of big data applications. By analysis of the big data, it is valuable for not only more efficient project delivery but also for all the stakeholders to obtain operational benefits. Big data analysis methods include statistical analysis, online analytical processing (OLAP), and data mining. Statistical analysis and OLAP [35] are based on the structured query language (SQL) for relational databases (or data warehouse). Data mining is a process of extracting valuable information hidden in big data through a set of algorithms, which is appropriate for both relational and NoSQL databases [36]. The data mining algorithms are highly related to machine learning, which will be will be discussed in detail in Section III.E. Visualization can vividly show the analysis results of big data in the forms of charts, images and animations, which help users to gain deeply insights and make decisions. Although there are numerous available open-source and web-based data visualization tools, for the construction industry, highly heterogeneity of the data is still a challenge for its visualization. Furthermore, it is a valuable research direction that can be combined with BIM technology to realize location-based visualization, e.g., to intuitively display the highly risk area in a BIM model.

E. MACHINE LEARNING

Machine learning is a sub-field of artificial intelligence that enables computers to simulate human learning and independently obtain knowledge by summarizing complex phenomena [37]. In a practical sense, machine learning is a method of training models for prediction through data. Based on the different types of data, machine learning can be divided into unsupervised and supervised learning. For unsupervised learning, data is not specifically identified, and learning models are designed to infer some of the intrinsic structure or regular pattern of the data. Common unsupervised learning methods include learning the association rules and clustering. In supervised learning, the input data is referred to as ‘‘training data,’’ and each group of training data has a clear label. Common supervised learning methods include regression analysis, decision trees, support vector machines (SVMs), and artificial neural networks (ANNs). Deep learning is a new research direction in the field of machine learning, which is the development of artificial neural networks [38]. With the increasing amount of training data and cheaper computing resources, ANNs are used to build more complex neural networks for deep learning. The representative deep learning models include the deep belief network (DBN), recurrent neural network (RNN), convolutional neural network (CNN), long short-term memory (LSTM), and their combinations.

Machine learning is one of the most important big data mining technologies, and most data mining algorithms are related to machine learning methods, which have many applications for construction. For example, Fan *et al.* [39] developed a construction case retrieval system using clustering to identify past safety accidents. Trost and Oberlender [40] adopted multivariate regression analysis for predicting the project cost in the early stages of construction. Fang *et al.* [41] combined a back-propagation algorithm and a heuristics-based tunable steepest descent method for training an ANN to detect structural damage. Efficient machine learning methods contribute to the excavation of the value of data. Meanwhile, a successful machine learning application also requires massive data, and a greater amount of data contributes to improving the accuracy of machine learning models. Thus, machine learning and big data are complementary trends, with the former for exploring the value of massive data and the latter for enhancing the performance of the former.

F. INTELLIGENCE COMPUTING

Optimization problems widely exist in the construction industry, such as the resource constrained project scheduling problem (RCPSP), construction scheme selection, site layout, and material logistics management [42]. The optimal algorithm of a problem may find the optimal solution of each instance theoretically, but when facing complex engineering problems, the computation cost is often unacceptable. Moreover, many engineering problems are often described in very vague terms, which are difficult to express with accurate models. Intelligence computing is a branch of artificial intelligence technology that aims to create a system with an independent thinking ability by imitating human thinking or the laws of the natural world, which has a wide application prospects in the optimization problems of the construction industry.

To balance the computation cost and accuracy of the optimization problems, computer scientists have proposed many intelligent algorithms with heuristic characteristics [43]. The term ‘‘heuristic algorithm’’ refers to a kind of algorithm inspired by the laws of nature or problem-oriented experiences and rules, which can provide a feasible solution with a reasonable cost. The commonly used heuristic algorithms include the tabu search, simulated annealing, genetic, ant colony optimization, particle swarm optimization, and artificial fish swarm algorithms. Because of their strong parallel computing and global search capabilities, as well as their adaptive abilities and robustness, heuristic algorithms are widely applied in the optimization of complicated engineering problems [44]–[46]. Despite this, there are still many drawbacks at present. For instance, they often depend on user experience but lack mathematical foundations, they lack effective iteration stopping conditions, and the convergence rates are difficult to control. To overcome these drawbacks, on one hand, the basic theory of heuristic algorithms requires further study, and a unified and complete theoretical system should be established in the future. On the other hand, for specific engineering problems, they should be combined with other intelligent technologies to overcome the drawbacks of the heuristic algorithms.

G. REASONING TECHNOLOGY

Reasoning technology is an important branch of the decision support field. Since the 1980s, many scholars have attempted to establish an expert system to study the mechanism of rule-based reasoning (RBR) to assist the decision-making of construction management [47], [48]. The performance of an expert system depends on the knowledge rules it contains. The number of rules is finite, but the number of possible situations is infinite when engineering problems occur. Due to the lack of sufficient rules, the application of an early expert system in the construction industry was not very successful. As discussed in Section III.E, with advent of the big data era, the rise of machine learning has enabled automatic knowledge acquisition based on historical data [49]. Nonetheless, the knowledge in the construction industry is often fuzzy and uncertain and difficult to express by accurate rules. Fuzzy reasoning, also known as approximate reasoning, is a reasoning process of drawing possible uncertain consequences from imprecise antecedent sets. In recent years, many fuzzy reasoning expert systems have been developed for assisting decision-making in the fields of construction management, such as risk assessment [50], [51], productivity forecasting [52], [53], and cost analysis [54]. The advantage of fuzzy reasoning is that it not only has sufficient adaptability and robustness, but it can also be used for heuristic and exploratory reasoning. Thus, it is suitable for dealing with complicated and uncertain engineering problems.

In practice, an expert (engineer or manager) often makes judgements and decisions based on his/her own experience when facing engineering problems. Experts have rich experience because they have encountered and solved many historical cases. When encountering new problems, they compare them with cases in their memories, analyze their similarities and differences, and obtain inspiration. This process is actually a mechanism of case retrieval and reuse. Case-based reasoning (CBR) is an artificial intelligence technology that simulates human analogical thinking using a computer [55]. It provides a reference scheme for solving new problems by retrieving and reusing similar cases in case databases, especially in areas where theoretical knowledge is difficult to express or causality is difficult to grasp but a large amount of historical data has been accumulated. Compared with an expert system, CBR does not need explicit knowledge rules but directly acquires experience from historical data, which will gradually gain advantages with the continuous accumulation of big data resources of the construction industry [13]. In recent years, CBR has been gradually applied to construction scheme design, cost estimation, tendering and bidding, contract management, risk assessment, and dispute settlement [56] of construction projects. The case reasoning process is divided into retrieval, reuse, revision, and retention, also known as the 4R process. A case consists of various attributes, and the similarity between cases is defined by the similarity between attributes. The key to engineering case retrieval is the representation and analogy mapping of a project case. Many studies have contributed to the representation and similarity mapping of engineering projects, such as the characteristic tree method [57] based on meta-synthesis and the geometric feature matching technique based on BIM models [58]. For the case automatic revision mechanism, the comparatively mature method is to adopt heuristic algorithms [59], [60] by optimizing the retrieved source case scheme to obtain a more suitable scheme for the target case.

H. 3-D RECONSTRUCTION

The 3D reconstruction technology describes the real scene as a mathematical model that conforms to the logic expressions of computers through the process of depth data acquisition, preprocessing, point cloud registration and fusion, and surface generation [61]. The point cloud refers to a set of data points obtained from data sources (e.g., a laser scanner) in a 3D coordinate system, which are used to represent the external surfaces of an object [62]. A laser scanner carried on an unmanned aerial vehicle (UAV) has been reported to be effective for obtaining panoramic data of a construction site in real time [63], [64]. However, the 3D surface model only presents the surface shape of the components but does not contain their other attributes. Therefore, it must be transformed into an information rich and object-oriented BIM model, i.e., a real-time construction model. The manual conversion is a time-consuming and error prone task. Wang *et al.* [65] presented a method for automatically extracting the building geometries from an unorganized point cloud. Brilakis *et al.* [66] proposed a framework to realize the automatic creation of real-time construction models by identifying the building-related components and automatically converting them to entity components with object attributes. The obtained real-time construction model could act as the digital twin of the building under construction.

I. VIRTUAL REALITY AND AUGMENTED REALITY

In virtual reality (VR), a person is immersed in a special environment generated by computer technology, giving him/her unique insights into the real world. Project participants use virtual reality to visualize and understand engineering problems to reduce uncertainty. At the design stage, VR can be used for risk assessment, spatial layout, lighting design, and landscaping, and during the construction process, it can be used for construction scheme evaluation, construction scheduling, site layout, and construction processes monitoring. The combination of BIM and VR will create new possibilities for developing an efficient communication platform [67] that enables project participants to understand the project from a first-person perspective, especially those lacking expertise or experience. Du *et al.* [68] developed a BIM-VR real-time synchronization system based on cloud computing technology for the collaborative decision-making of project participants. Boton [69] proposed a VR-based collaborative BIM 4D simulation framework for supporting constructability analysis meetings. VR in combination with BIM can also create a risk-free training environment for visualized labor training, skill transfer, and safety education [70], [71].

Augmented reality (AR) is an interface that overlays digital information onto the user's field of view, spatially aligned to the current physical world environment. It establishes a connection between a virtual world and the real world, while keeping the flexibility of the virtual world. With augmented reality, virtual content can be seamlessly integrated into real scenes, thereby enhancing the depth of human perception of the environment and enhancing the ability for humans to control the outside world [72]. During the construction process, virtual information can be superimposed on the real construction environment using augmented reality technology, which enables workers intuitively obtain the environment status and better understand the operation procedures and safety regulations. For deploying AR to a complicated construction environment, several critical technologies must be considered [73], [74]. First, accuracy localization technology plays a significant role in superimposing the information onto construction objects. Second, because they are faced with heavy construction tasks, workers could be required to use portable wearable devices (e.g., AR glasses) to interact with the augmented reality and allow them to send instructions in a convenient way, such as through voices or gestures. Third, combining BIM with AR will contribute to feeding cyber information back to the construction site, especially in the indoor environment. Finally, deploying the AR applications in a cloud service and integrating with big data will contribute to enabling workers to obtain more and consistent virtual information, similar to viewing information through a web browser.

IV. PROPOSED CYBER-PHYSICAL SYSTEM FRAMEWORK

This paper presents a framework of the cyber–physical system that integrates the above-mentioned technologies for improving the overall capabilities of construction organization and management, as shown in Figure 1. The physical part is a flexible and reconfigurable architecture, all construction resources (e.g., workers, materials, and equipment) are plug

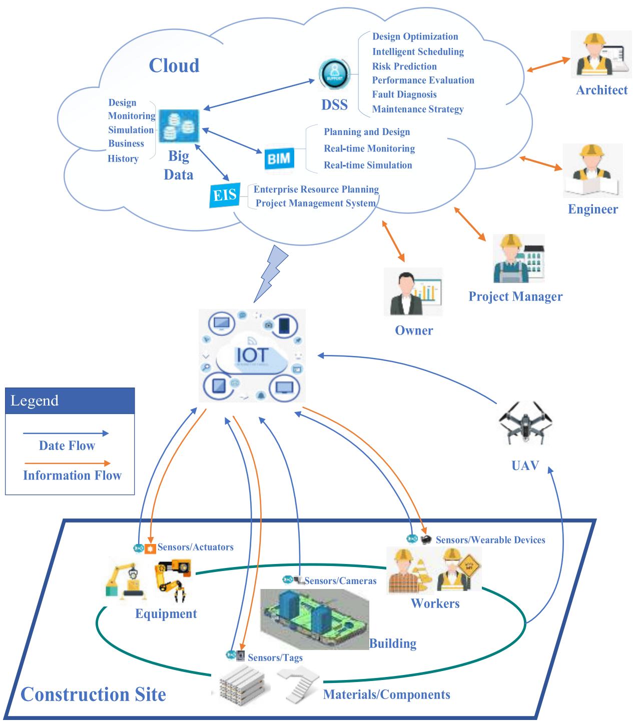

FIGURE 1. **Overall framework of the cyber-physical system.**

and play, homogeneous resources that can be substituted for each other. The heterogeneous resources can work in coordination, and the access or departure of any one resource will not affect the overall performance of the system. IoT links the physical construction site with the cyber part to achieve the cyber–physical vertical integration [75]. The cyber part is deployed in the cloud, which provides PaaS for the big data storage and analysis and SaaS for the application software, such as the BIM, decision support system (DSS), and enterprise information system (EIS). The cloud-based solution allows all participants to quickly access the CPS through different terminal devices (e.g., mobile or wearable devices) to obtain information of interest. Furthermore, it enables them to think about problems from a common perspective (e.g., by immersing them in the same virtual reality environment) to eliminate their cognitive differences and promote collaboration.

To realize the interaction and mapping between the physical and cyber components, a digital twin of the construction site should be introduced to the CPS. Figure 2 shows the model of the digital twin in the proposed CPS framework, which includes three parts: the physical construction site, the cyber model, and their connections. The cyber model is the real-time construction model in the BIM software, which integrates the digital models of the buildings in terms of the construction, workers, equipment and materials based on the data integration standard of IFC. The digital twin enables the seamless integration between the cyber computations with physical processes in a feedback loop where a physical process affects a cyber computation and vice versa [76]–[78]. Interoperable data tightly connect the

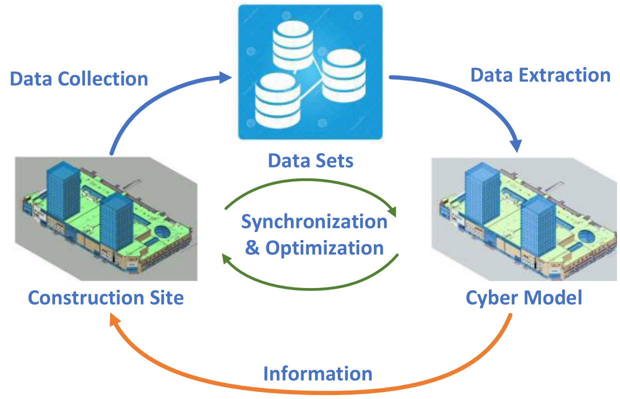

FIGURE 2. **Digital twin model of the proposed CPS framework.**

construction site with its cyber model for cyber–physical interactions and collaboration [79]. The cyber model can be optimized during synchronization with the construction site by collecting and extracting its data, while the latter can be dynamically adjusted by receiving the information from the former. During the practical construction process, the state of the construction site is sent to the cyber part of the CPS in real time, after which it performs monitoring, simulations, and decision-making and feedbacks the control information. The detailed descriptions will be introduced in the following subsections.

A. REAL-TIME MONITORING AND RESPONSE

Figure 3 presents the real-time monitoring and response process in the proposed CPS framework. The IoT provides ubiquitous sensing capabilities to collect data from a construction site. Different types of sensors collect real-time data from the construction site, including the stresses and displacements of structures, the temperature and the air quality on site, energy consumption, and the status of construction equipment [80]. Wi-Fi or Bluetooth techniques are used to connect the wireless sensors deployed in the construction site to form a wireless sensor network [81]. RFID is used to collect real-time data in the whole process of prefabrication construction-site assembly by tracing the tag embedded in the components [82]. RFID, Zigbee, and the ultra wide band (UWB) techniques can be adopted for indoor personnel positioning, while outdoor positioning can be achieved through the global positioning system (GPS) [83]. The UAV carries a laser scanner to obtain the point cloud data of the construction site to monitor the construction progress based on 3D reconstruction technology. Cameras capture images of the construction work on site for recording and analyzing the construction process. Wearable devices integrate the functions of sensors, cameras, and mobile locators to collect the working status of workers on site [84].

IoT links the monitoring data from a construction site to the cloud platform, as shown by the blue line in Figure 1. The real-time construction model acts as the cyber model (i.e., digital twin) of the construction site, with the 3D

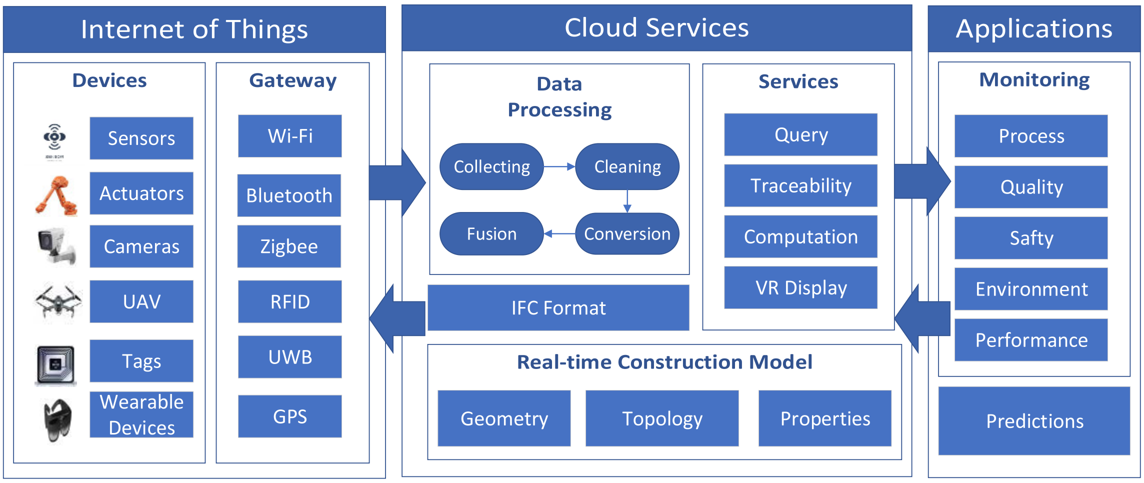

FIGURE 3. Process of real-time monitoring and response in the CPS.

model generated from point cloud data. It automatically associates BIM-related components to achieve real-time updating. Heterogeneous data collected from different data sources should be cleaned first to remove noise and invalid data [85], converted to a unified IFC format, and then fused with the geometric data of a real-time construction model. The real-time construction model presents the spatial topological structure of the monitoring data to project participants for visualization, enabling them to cooperate from a common perspective and thinking mode. The cloud platform provides monitoring data query, traceability, computation, and virtual reality display services for different project participants to support their monitoring requirements on project progress, quality management, safety and environment supervision, and performance evaluation.

Benefiting from real-time monitoring, the project management team can supervise the complicated construction process and perform rapid adjustments or optimization. In addition, the real-time monitoring also contributes to making real-time predictions [86]. For instance, as described in Subsection II.E, lacking real-time information often makes it impossible for workers to react in a timely manner when confronting dangerous situations. Under the proposed CPS framework, comprehensive monitoring of the physical process in real time enables the cyber part to identify or predict risks ahead of time [87] and feeds back the alarm information to the workers in time. The cyber part feedbacks control instructions to the physical part through the IoT, as shown by the orange line in Figure 1. Actuators embedded in construction equipment are responsible for receiving and executing these instructions [88]. The on-site workers can receive information through wearable devices [84], e.g., displaying the operation instruction, warnings, or remote assistance information in AR glasses. From the above analysis, CPS is a closed-loop ecosystem of "perception calculation feedback," which is similar to the nervous system of an organism.

B. REAL-TIME CONSTRUCTION SIMULATION

Traditional 4D simulations in BIM are performed after the design and before the construction starts based on the as-planned data, which remains at the level of visual communication rather than acting as the promoter for planning, analysis, and decision-making [89]. The uncertainty in the unstructured construction process is not considered, often causing the output results to differ significantly from the actual situation. Moreover, dynamical simulations during the construction progress are not possible due to the inability to incorporate real-time data into the existing BIM models [66]. To overcome these limitations, we present a simulation approach based on the proposed CPS framework, which adopts the real-time monitoring data as input data for the simulation.

Figure 4 presents the real-time simulation approach during the construction progress, which simulates the execution of the remaining tasks based on the current working status. The input data of the simulation includes the following three components: 1) a real-time construction model, where the automatic updating mechanism based on real-time monitoring data was discussed in Section IV.A; 2) construction constraints, including space constraints (e.g., inventory and the yard and construction workspace), resource constraints (e.g., the usage status of the non-consumable resource, or available quantity of consumable resources), and logical constraints (logical relationship and time intervals between tasks). Constraints change dynamically with the construction process, the monitoring data collected from a construction site contribute to updating the constraints in a real time. Furthermore, the project management team can also adjust the constraints based on their experience; 3) just-in-time (JIT) plans [90], which includes WBS, the project schedule, and resource planning. The WBS is used to hierarchically decompose the construction work into smaller and easier-to-manage construction tasks and to establish a framework for the formulation of project plans.

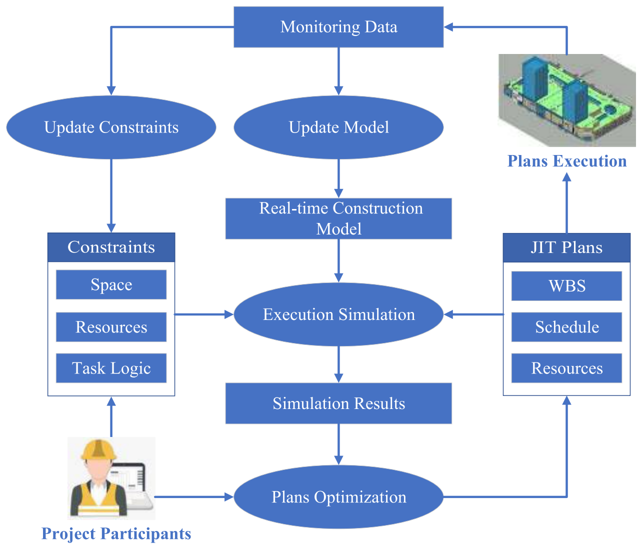

FIGURE 4. Real-time simulation during construction progress.

The project schedule defines the planned start and end times for each task, while the resource plan assigns the construction resources required for each task. Unlike the traditional project plan, a JIT project plan can be adjusted and executed dynamically as the project progresses.

Discrete event simulation (DES) method is used to verify the project plans [91]. The simulation results include the plan feasibility, potential conflicts, productivity dynamics, and resource utilization. Real-time simulations reinforce the collaboration between project management team, while the simulation results are a significant data resource to support their decision-making, which will be further discussed in the following subsections. The project management team makes assessments and improvements based on the simulation results in a timely manner, works out optimized JIT project plans, and sends them to the construction site for execution. Therefore, the process transitions from data monitoring to real-time simulations, then to the optimization of the project plans, until the plans are fed back to the site for execution, forming an iterative optimization cycle to deal with the uncertainty in the construction process.

C. DATA-DRIVEN DECISION SUPPORT SYSTEM

Most decision making in construction management is made by decision makers based on the manual collection of information. This work is labor intensive, error prone, and heavily dependent on the rules of thumb and experiences of the decision makers [13]. The rules of thumb and previous experiences are defined as tacit knowledge because they are hard to capture, formalize, and make explicit [92]. The essence of the data-driven decision support system is to automatically discover tacit knowledge from mining the collected data and then support the decision-making of the current projects combined with intelligent technologies. Figure 5 presents the architecture of the data-driven decision support system in the proposed CPS framework, which consists of three layers: the data source layer, data processing layer, and data application layer.

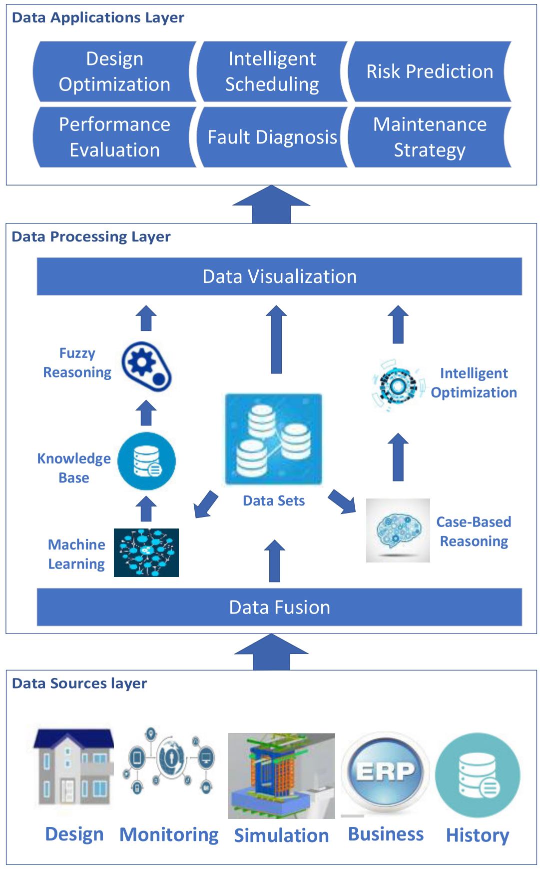

FIGURE 5. Logical architecture of data-driven decision support system.

The data source layer consists of the design and simulation data from the BIM, construction monitoring data from the IoT, business information system data, and historical project data. In the data processing layer, these data are extracted and cleaned, redundancies are removed, and the data are converted to an analyzable format, i.e., data fusion. The fused data are used for analysis to support decision making. On one hand, tacit knowledge is acquired through machine learning, which can generate decision suggestions based on fuzzy reasoning mechanism. More specifically, benefitting from the real-time monitoring data collection in the CPS, it is possible to analyze data over time to capture their time dependence and obtain temporal knowledge. In contrast to static knowledge, temporal knowledge plays a significant role for characterizing the dynamics in the construction progress [93], e.g., the activity duration is calculated by comparing the timestamps corresponding to the events. On the other hand, based on the case-based reasoning technology, similar cases to the current project can be retrieved from the historical project data. The solutions of similar cases can be used as the reference scheme of the current project after adjustment and optimization. The results of reasoning and direct statistical analysis of the fused data are displayed to users in the form of visualization to support the decision-making requirements of different users, which include design optimization, intelligent scheduling, risk prediction, performance evaluation, fault diagnosis, and proactive maintenance strategies.

The significance of data-driven decision support for engineering projects is that it makes the best use of historical project data. Benefitting from the cloud solution, data sharing and knowledge transfer across projects are available. After systematic processing, historical project data are transformed to information for explaining the uncertainty and further extracting knowledge for guiding future work [5]. In this sense, the continuously accumulated historical data will become strategic resources for decision making.

V. APPLICATION CASE STUDY

As forward-looking research, it is difficult to choose a real case that covers all the innovative ideas of this study. Nonetheless, we present a project of the Xiong'an citizen service center to verify the technological feasibility and preliminary implementation effect of the proposed CPS framework. The Xiong'an New Area was established by the Chinese government in 2017, with the purpose of undertaking Beijing's non-capital functions to relieve its growing pressure. As the future administrative center of the Xiong'an New Area, the Xiong'an citizen service center covers an area of 242,400 m^2, with a total construction area of 100,200 m^2. It consists of seven 2-5-storey steel structures and one 3-storey integrated modular house. As a pilot project to promote intelligent construction, multiple intelligent technologies have been integrated into the engineering construction, forming a prototype of the CPS for construction. The technical measures, implementation effect, and improvement directions of the case study are discussed below.

A. TECHNICAL MEASURES

Table 1 shows the main development environment for establishing the cyber part of the CPS. Visual Studio was adopted as the development tool of the application software because it has rich graphic components and supports the efficient development of applications in the C# language. Due to its better compatibility with Visual Studio, SQL Azure was selected as the database service deployed on the cloud platform. Autodesk Revit was adopted as the BIM tool to develop a design model and related real-time construction model, which could integrate with SQL Azure through its plug-in DB Link and support secondary development with the C# language. Revit Live is software that generates a VR scene through a 3D model. A model developed by Revit can be transformed into an immersive VR environment through a simple configuration. The cyber part of the CPS is deployed on the cloud platform based on the Widows Azure operating system, which supported for remote access for the project participants.

TABLE 1. Development environment of the cyber part.

Development Environment	Adopted products
Cloud Platform	Widows Azure
Database Service	SQL Azure
Development Tool	Visual Studio
BIM Software	Revit
VR Software	Revit Live

Figure 6 shows the UAV with a radar scanner (integrated functions of laser scanning, camera and orientation) to capture the point cloud data of the construction site and generate a 3D reconstruction model, after which it was matched with the BIM design model to obtain a real-time construction model. As shown in Figure 7, as the digital twin of the physical construction site, the real-time construction model was used to visually monitor and simulate the construction process, and provide a unified perspective for the cooperation and decision-making of all project participants.

FIGURE 6. UAV with a radar scanner.

FIGURE 7. Digital twin of the construction in progress.

GPS technology was used to locate workers, as shown in Figure 8. The GPS receivers were installed on workers' helmets to capture their locations in real time. The collected location data was transmitted to the cyber part and then integrated with the real-time construction model. Figure 9 shows a heat map of the location of 1018 workers during construction, which helped the project managers to understand the current busy work area and labor dynamics. The distribution of workers could also be viewed by type of work or subcontractor to coordinate their work.

A construction environmental monitoring system was deployed on the site, as shown in Figure 10. It was integrated with wind-force, wind-direction, temperature, humidity,

FIGURE 8. Helmet mounted GPS receiver.

FIGURE 9. Heat map of workers' location distribution.

FIGURE 10. Environmental monitoring system of the construction site.

dust sensor, and noise sensors. The collected sensor data was transmitted to the cloud platform through Internet for remote environmental monitoring. Figure 11 shows the environmental monitoring interface of the cyber part. All project participants could obtain the real-time status of the site environment by accessing the cloud services. This function was also used by the environmental protection department to monitor the environmental conditions of the construction site, and evaluate the environmental performance of the contractor through historical monitoring data.

RFID technology was applied to prefabricated component tracking and management. As shown in Figure 12, an RFID tag was embedded in each component when it was produced, which recorded its unique id as well as the design and

FIGURE 11. Interface of visual decision-making support.

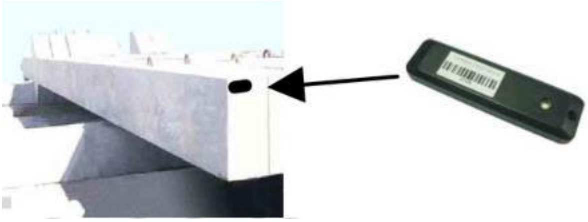

FIGURE 12. RFID tag embedded in a concrete component.

production data. The tag will be used to trace the component throughout its whole lifecycle and record relevant data by interacting with RFID readers. The RFID reader generated an electromagnetic field by transmitting RF energy to the identification area, activated the RFID tags and exchanges information with it, and finally sent the identification information to the cloud platform through a network connection [94]. Figure 13 shows the interface of the component tracing and management in the cyber part, which benefited from the real-time collection of the component status data. Project managers could monitor the quantity of different types of components during production and transit as well as those had arrived and had been installed. Furthermore, the monthly and total statistics of component usage could also be obtained based on the historical monitoring data.

FIGURE 13. Interface of component tracing and management.

RFID technology was also applied for construction quality monitoring. After installation of a component, the quality inspector read the component information stored in the RFID tag through a hand-held reader and uploaded the quality inspection record to the cyber model. The inspection record data was linked to the real-time construction model through the component identity. As shown in Figure 14, project managers could view the quality inspection record by clicking a component. In addition, the real-time statistical results based on the quality inspection data were displayed in a visual form, and the weekly generated quality management report was also displayed to assist project managers in decision making.

FIGURE 14. Construction quality monitoring.

VR-based construction simulations were available in the CPS. The project management team formed by a contractor and subcontractors could access the real-time construction model of the cloud platform to conduct a real-time construction simulation, which enabled them to cooperate with each other based on a common perspective. As shown in Figure 12, virtual reality technology combined with BIM immersed them in a virtual construction environment for construction scheduling, site layout, safety assessment, and coordination of subcontractors. The VR-based real-time construction model was also used for the safety training of workers, especially those who were exposed to dangerous conditions, such as those working at large heights.

FIGURE 15. Construction simulation based on virtual reality.

B. IMPLEMENTATION EFFECT

Figure 16 shows a picture of the Xiong'an citizen service center, which benefited from real-time progress monitoring and construction scheduling based on the CPS. The project was completed as scheduled with a construction period of only 112 days. The CPS realized the whole process monitoring of the supply chain of prefabricated components, which contributed to the close cooperation of the production, logistics, and assembly process. Construction quality problems could be traced to specific components in real-time, which eliminated the lag of quality inspection information. In addition, CPS enabled all project participants to understand the problems in the construction from a common perspective, and the construction simulation based on the real-time construction model contributed to strengthen the cooperation between contractors and subcontractors. Moreover, the implementation of CPS was of great significance for promoting sustainable construction. For example, because contractors knew the fact that the site environmental conditions were being monitored by the environmental protection department, they had to consciously strengthen the environmental protection measures during construction.

FIGURE 16. Xiong'an citizen service center after completion.

C. IMPROVEMENT DIRECTIONS

Although the technical measures and basic functions of the proposed CPS framework were preliminarily realized in the project of the Xiong'an citizen service center, there were still some limitations that requires further improvements. On one hand, the monitoring objects of the CPS cover the buildings under construction, workers, components, and construction environment, but the construction equipment was not monitored in this project. In fact, the operation status data of the main construction equipment could be monitored by the sensors and integrated with the real-time construction model for performance evaluation and construction safety warnings. On the other hand, the data-driven decision-making is limited to statistical analysis and data visualization, and the capacities of knowledge acquisition and reasoning are still weak. Further study should focus on developing algorithms and models to discover new knowledge or predict future trends based on the historical monitoring data [95]. Moreover, optimization of construction organization modes based on the application of the CPS should be further explored. For example, how to dynamically adjust the production and transportation plan based on the assembly of components on construction site should be examined to improve the production efficiency and reduce inventory costs.

VI. DISCUSSION AND PROSPECTS

In the context of Industry 4.0, the implementation of the CPS in the construction industry will contribute to the transformation of the project management paradigm. As discussed in Section II.D, the traditional project management mode requires the construction scheme to be made in as much detail as possible in the planning stage. However, due to the complexity and high uncertainty, the more detailed the scheme is, the more deviation is possible from the plan in the actual implementation process. Benefitting from real-time monitoring, simulations, and the decision support mechanism of the proposed CPS, future construction plans will no longer be fixed and predefined, but it will be possible to make and adjust the plans according to the actual situation in the construction process. On this basis, dynamic scheduling and control can be implemented to improve the construction resource utilization and reduce waste, which will be consistent with the just-in-time production mode of the manufacturing industry [96], [97].

The CPS will also reshape the value network of the construction industry, i.e., the original intention of Industry 4.0. Through horizontal integration, all entities involved in the process of value creation can be connected to the CPS, and all relevant information can be obtained in real time, thus forming a dynamic, self-organized, and real-time optimized value network that supports cross-organization collaboration for maximizing the project value. In this sense, the production organization mode of the construction industry will tend to be homogeneous with that of the manufacturing industry [98].

From a technical perspective, Industry 4.0-related technologies are built with highly heterogeneous hardware and software, which is an enormous challenge for their integration. To implement the proposed CPS, an interdisciplinary team should be established, because no one can grasp each technical detail. Architects, civil engineers, and project managers might need to work with computer scientists and artificial intelligence experts. With the diversification of application scopes, the range of disciplines required will constantly expand. It is predicted that professional CPS integration service providers independent of project contractors will appear in the future to provide consulting services, scheme design, system construction, and technical support.

VII. CONCLUSION

This paper aimed to present a discussion on the integration of Industry 4.0–related technologies to establish a cyber–physical system for improving the overall capabilities of construction organization and management. The main contributions of this study are as follows:

(1) Based on the analysis of the characteristics of the construction industry and obstacles to its intelligent development, this paper provides a systematic overview of the research and application status of Industry 4.0–related technologies in the construction industry and their potential integration opportunities.

(2) A framework of the cyber–physical system is proposed in this paper, in which the real-time construction model acts as the digital twin of the building under construction. Furthermore, real-time monitoring and simulation and the architecture of a data-driven decision support system were discussed under the proposed framework.

(3) A case study of the Xiong'an citizen service center was introduced to verify the technological feasibility and preliminary implementation effect of the proposed CPS framework.

(4) We made horizontal comparisons between the construction and manufacturing industries throughout the article in the hopes of gaining valuable insights for future intelligent construction research, drawing on advanced trends and ideas in intelligent manufacturing. Meanwhile, we argued that with the deep integration of Industry 4.0–related technologies and the implementation of the CPS, the production and management modes of the construction and manufacturing industries will gradually become increasing similar.

As forward-looking research, this paper may also to inspire more efforts in this field.

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