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SURVEY

Virtual Prototyping for Modern Internet-of-Things Applications: A Survey

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ABSTRACT Modern technological industries fused with the Internet-of-Things (IoT) have been advancing rapidly. The joint usage of several technologies has led to the reshaping of the modeling and simulation techniques into the virtualization of physical systems. Thus, the concept of virtual prototyping has emerged as a significant development in distributed IoT applications that includes early exploration, optimization, and security assessments. Several industries have been employing various types of prototyping *e.g.*, virtual platforms, digital twins, and application-specific virtualization techniques, to achieve individual needs for development. In this survey, we clarify some of these concepts and the distinctions between them, provide a comprehensive overview of various prototyping technologies, and discuss how several virtualization technologies play a transformative role in the design and operation of intelligent cyber-physical systems.

INDEX TERMS Digital twin, virtual platform, Internet of Things, cyber-physical systems.

I. INTRODUCTION

The Internet-of-Things (IoT) has gained popularity over the past ten years by evoking the idea of a worldwide infrastructure of networked physical things that would provide anytime, anywhere connectivity for anything and not just for any one person [1]. As technology evolves, more and more cyber components are getting integrated into the physical systems around us, incorporating more aspects of IoT. Embedded systems are used in most applications that monitor all physical mechanisms affecting computations and *vice versa*. Naturally, the integration of cyber and physical components of systems came up with terms and explored new vision *i.e.*, in the modern-day, what we call "a cyber-physical system" (CPS) [2], [3], [4]. Furthermore, IoT revolves around "smart systems" — an ability to gather and apply knowledge independently — referring to the "things and sensors" that are intelligent, uniquely addressable, flexible, and autonomous with intrinsic security [5]. A shortened term for the industrial applications of IoT, commonly referred to as the Industrial Internet-of-Things (IIoT), is another concept reshaping the modularly structured smart factories of Industry 4.0 [6]. Additionally, conventional domains such as control systems, wireless sensor networks, and automation enable IoT systems both individually and collectively, particularly in the areas of privacy and security. Combining these concepts, IoT is revolutionizing modern industrial applications into a smarter domain, and more emerging technologies are being developed to contribute to that expansion.

The system-level exploration of IoT systems has gained significant attention nowadays. The spread of new technologies connected through the Internet inspired researchers to study physical systems at an abstract level. While modeling and simulation have been around with the rapid growth of the computer for several decades, structured prototyping of systems, sub-systems, and components as a virtual counterpart is a recent development. There are several terms in common industrial use — *virtual prototype, virtualization, virtual platform, digital twin, virtual replica, digitalization, modeling, simulation, etc.* that, albeit similar, have somewhat nuanced and different interpretations and apply to slightly different contexts. In the context of IoT and software modeling, virtual prototyping is an engineering discipline that involves modeling, simulating, visualizing, or abstracting a software, hardware, or overall physical system based on its fully functional operating behavior. It allows any real-world system or

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component to be mimicked into a virtualized version that can be explored freely. The integration of instruction-set simulators, hardware building block models, numerical analysis, and twining techniques has motivated us to achieve more advancement.

In spite of its critical need, there is no comprehensive survey providing a generic overview of different kinds of virtual prototyping technology for various IoT applications in the industry. Consequently, it is a daunting task for a researcher or practitioner getting started in this area to sift through the mass of research articles across journals and conference proceedings, often spanning disparate applications with their own rich bodies of literature, to assimilate the information about the state of the art. In this paper, our goal is to fill this crucial gap. We explore the variety of prototyping techniques, including digital twins, virtual platforms, and various domain-specific infrastructures, point out the key differences and the contexts of their application, and discuss emerging prototyping technologies from various domains. Fig. 1 shows a taxonomy of the virtual prototyping overview. We show how these prototyping techniques are shaping the IoT application industry to enable advancements, *e.g.*, replication of the individual components, features, processes, and dynamics of physical systems in the digital environment, with improved control over testing, analysis, forecasting, and risk mitigation.

The remainder of the paper is organized as follows. Section II discusses various technical challenges with prototyping. Sections III and IV discuss two specific prototyping methods, virtual platform, and digital twins. Section V presents an overview of enabling technology for virtualization. In Section VI, we discuss various applications of virtual prototyping methods. We conclude in Section VII.

II. TECHNICAL CHALLENGES

A. EXPLORATION OF CYBER-PHYSICAL SYSTEMS

The design of any cyber-physical system is a challenging task as it requires going over a set of CPS configurations involving, software, hardware, and integration. Major CPS like autonomous automotive systems, medical monitoring, smart grids, industrial automation, etc. face hard-to-detect errors that can induce major drawbacks later in the design, compromising reliability, efficiency, and safety. This demonstrates the inherent complexity of dealing with the design of a CPS, as the types and heterogeneity of the components can vary across domains and applications [7]. With current industrial practice, it is hard to resolve design errors and bug fixes before the assembly and manufacturing of hardware and software components. The need for virtual prototyping emerges to solve this critical problem by exploring the corresponding cyber-physical system way early in the system life-cycle which can eliminate potential design errors. The CPS involves heterogeneous components that require close interactions in a virtual environment to determine several exploration aspects. The developed prototyping techniques will be readily available to the design engineers of embedded control systems to help them explore and better understand the overall system for both hardware and software functionalities.

The majority of current CPS development focuses on the physical layer of embedded systems or the potential applications of the CPS domain [8]. Without a clear bridge, it is unclear how the embedded systems of the physical layers will be used to supply real-time services to the application layer. The virtual prototypes of such systems aim to eliminate these discrepancies by establishing real-time monitoring and diagnostics. The prototype computation modules analyze associated data, inform the physical systems of their results, and if necessary, transmit control commands to modify the physical environment or adjust system parameters [9], [10].

B. OPTIMIZATION

When considering an IoT-based application as a dynamic operating system, optimization is essential for improving reliability, efficiency, and the application of key process parameters, thus ensuring a better operation. The option of virtual prototyping provides the appropriate framework to adaptively tune certain parameters without meddling with the actual system design *i.e.*, allowing us to perform seamless optimization techniques. Moreover, the integration of virtual prototyping and optimization approaches can obviously provide a promising tool for quickly resolving errors and making informed decisions. The best approach is to build a prototype that supports real-time synchronization of IoT components, cyber backbone, and physical systems. For instance, different data analytics can be integrated to manage data on the machine by establishing digital twins of the machining process (*i.e.*, mostly studied in manufacturing systems) [11].

Optimizing the physical one based on the virtual model is a well-practiced approach, especially in modern IoT industries like aviation (*e.g.*, tires, aircraft health, etc.) and manufacturing (*e.g.*, shop floor, plant automation, etc.). Prototyping frameworks can also help to improve the robustness of the cyber-physical system by providing the interdependence of cyber and physical networks to explore various nonlinear optimization models [12]. There have been studies that focused on the optimization of various domains like — virtual reality [13], simulation of virtual platforms [14], [15], network function virtualization [16], [17], digital twin for production [18], [19], [20] etc. These approaches can eventually result in higher efficiency, highly advanced, and intelligent IoT systems with less complexity, provided the optimization techniques perform well.

C. SAFETY AND SECURITY

Current industry practice incorporates only a partial form of safety and security based on isolated networks and access control environments [21]. Cybersecurity is a major concern in IoT-enabled systems, which may be vulnerable to a wide range of cyber-attacks from potential adversaries. As a result, cybersecurity is essential for smart systems to succeed in

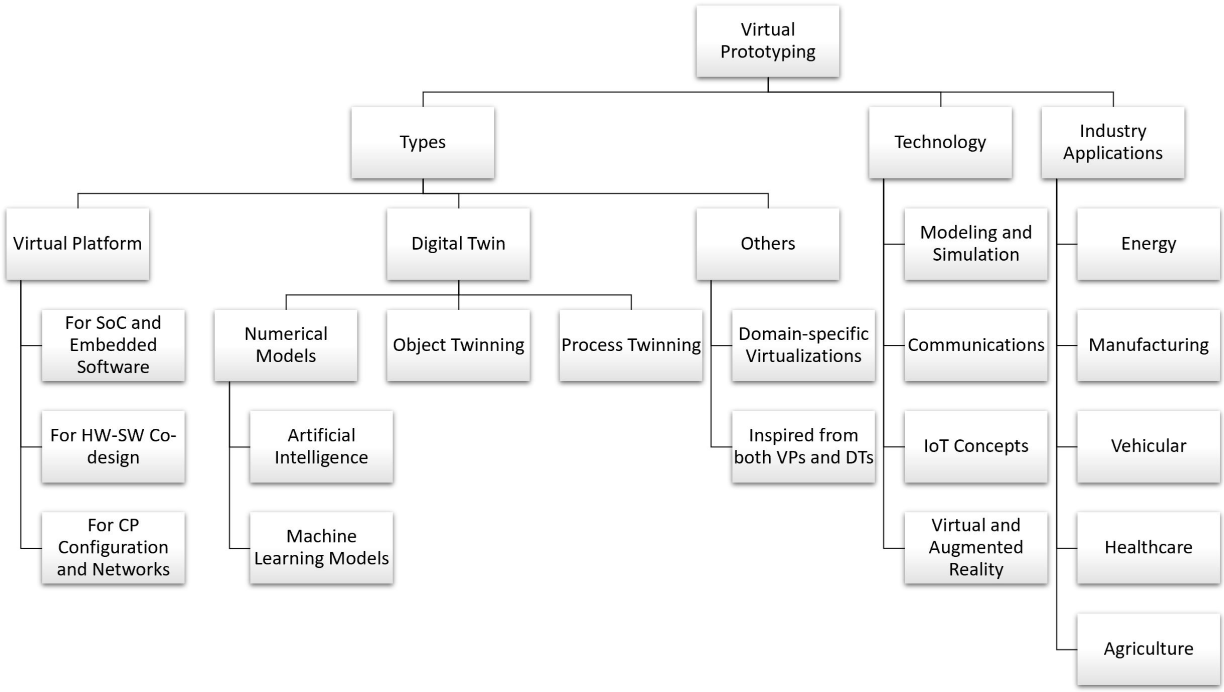

FIGURE 1. **A taxonomy of virtual prototyping overview.**

various industry applications. Theft of trade secrets and intellectual property, hostile data modifications, and disruptions or denial of process control are all genuine, worldwide, and growing cyber risks to the Industrial IoT systems [22]. Usually, security assumptions are made to design and operate the IoT infrastructure that might be at risk of not being fully technologically capable of eliminating potential security threats. Given this insight, virtual prototyping is implemented to evaluate the security vulnerabilities of primary system design, security software, and other IoT configurations, aiming to make them secure against first-order attacks [23]. A prototyping infrastructure can help to explore situations of accidental failure in order to avoid hazards and thus maintain the overall system's safety.

Several studies have attempted to address the safety and security needs using prototyping of respective IoT systems. For instance, Almeaibed et al. [24] sought to find a common framework for digital twins of vehicles that facilitates the analysis of a vehicle follower model to promote safety and security in autonomous vehicles. Alcaraz and Lopez [25] explored the current state of the DT paradigm by categorizing potential threats associated with it and offering a preliminary set of security recommendations. Lou et al. [26] proposed conducting a functionality and cybersecurity analysis based on the digital twin of an Industrial Control System (ICS). We understand that, when aligned with a virtual framework, the IoT infrastructure can be explored independently and function together to provide a solid foundation for an intelligent IoT application, while eliminating any shortcomings in the safety and security assessment.

III. VIRTUAL PLATFORMS

The idea of virtual prototyping has been popular in the cyber world, targeting system-on-chip designs, embedded software, and digital hardware. This prototyping approach is well known as a virtual platform (VP). It is a software-based modeling system that can completely mimic the functionality of a specific SoC or board. It can combine high-speed processor simulators with high-level, fully functional models of hardware building blocks in order to provide software developers and system architects with an abstract, reconfigurable representation of the hardware. This approach has been valuable for early software and hardware development, verification and validation, and hardware-software co-design [27], [28]. Because of their high levels of controllability and observability, VPs today provide a powerful debug infrastructure [29]. While, VPs are used mostly for the smaller sub-systems (*e.g.*, SoCs), they indirectly contribute to the larger IoT infrastructures that incorporate the target components being used for developing VPs.

A. VIRTUAL PLATFORMS FOR SoC AND EMBEDDED SOFTWARE

Modern cyber-physical systems incorporate embedded electronic components into a single integrated circuit that is known as a system-on-chip (SoC). The trend of SoC usage has driven constant technological advancements as it contains multiple processors combined within dedicated hardware. For rapid SoC development at an abstraction level, the need for a configurable virtual platform emerged. Today, the VPs

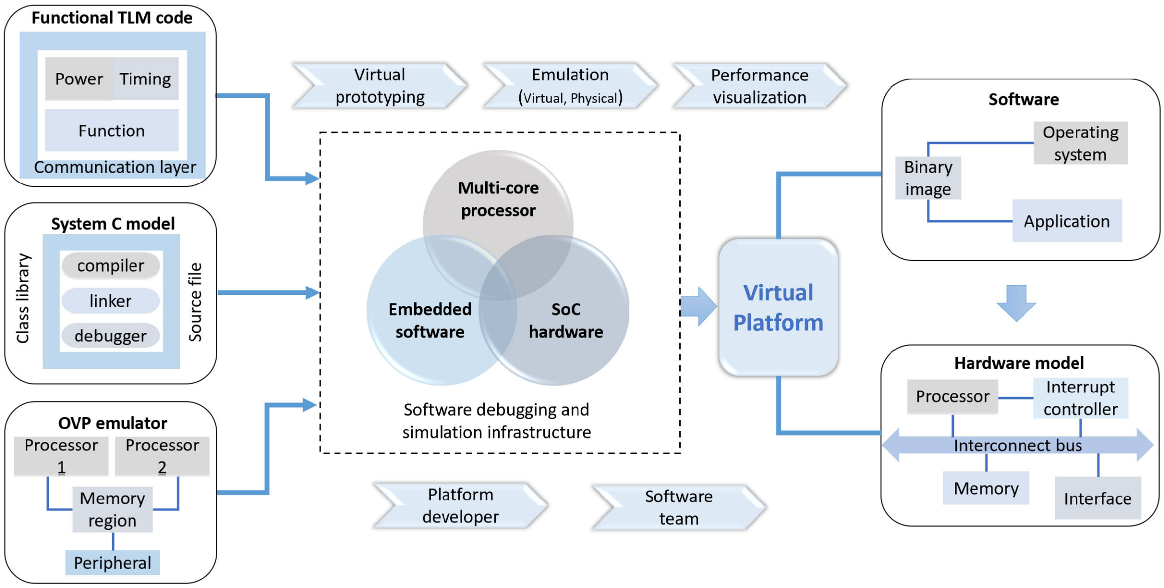

FIGURE 2. A conventional virtual platform activity. The functional TLM, SystemC models, and OVP emulators are the most common modes of developing platforms. The areas that utilize this technology are multi-core processors, embedded software, and SoC hardware. Abstraction of software runs on top of a hardware model that simulates the designated virtual platform.

are constructed using SystemC and transaction-level modeling (TLM) to further increase the abstraction level [30]. Given this insight, the authors conceptualized a virtual platform, *SoCRocket* [14], for the rapid SoC development in the aerospace domain. They developed a TLM-based framework where the core components have been modeled in SystemC. Their platform is available in three abstraction levels *i.e.*, loosely timed (LT), approximately timed (AT), and register-transfer-level (RTL). An integrated framework *SPHERE* [31], is introduced, targeting modern SoCs by abstracting the hardware complexity and virtualizing computational resources. SPHERE aims for the smooth operation of different subsystems on the same platform while providing a safe and secure functioning of cyber-physical system mechanisms.

VPs allow for early exploration and optimization of the embedded software development process by providing a high-speed framework *i.e.*, the ability to perform fast system simulations with only necessary functionalities in real-time. This means that the VP simulation framework must be fully instruction-accurate, with all interrupts and similar commands correctly emulated, and the peripherals and behavioral models must provide the proper functionality. Hong et al. [32] presented a case study of the VP application for a new hard disk system development known as *Hybrid-HDD i.e.*, one of the primary features of Windows VISTA. They summarized their model by comparing it with the conventional flow of software development, and explored software optimization via the VP. A conventional virtual platform activity in terms of three domains is depicted in Fig. 2 portraying the enabling technology of prototyping for mixed hardware/software development.

B. VIRTUAL PLATFORMS FOR HARDWARE/SOFTWARE CO-DESIGN

Throughout the SoC and embedded system design flow, verification and validation procedures ensure the requirements and specifications of software quality management and hardware/software co-design. Nowadays, researchers are moving towards using virtual prototyping platforms to solve both co-design and co-verification problems. A conventional VP for validation and hardware/software co-design is shown in Fig. 3, where the basic actions of the prototyping environment are depicted as a flow diagram. The modeling and simulation come into effect with the reference information and HW-SW configuration data for prototyping. After that, the virtual output gets validated based on the specifications of the prototyping basis and moves towards optimization. The invalid model goes through the HW/SW co-design process for refining, to be used again for simulation.

Lin and Su [33] discussed a heterogeneous virtual simulation platform targeting the system and functional level co-verification of SoC Software/Hardware Co-Design. They focused on functional and system-level verification by using an open-source emulator, *QEMU* to perform co-simulation within the SoC design flow. There are several researchers [34], [35], [36], [37], [38], who established virtual platforms using *QEMU* due to its ability to provide high-performance CPU emulation. Wicaksana and Tang [39], developed a virtual platform using SystemC with TLM and the Open Virtual Platforms (OVP) processor model with instruction set simulator (ISS) targeting multiprocessor system-on-chip (MPSoC) to fulfill the hardware/software co-design and verification requirements. Analogous to the conventional approach, they increased the abstraction level of

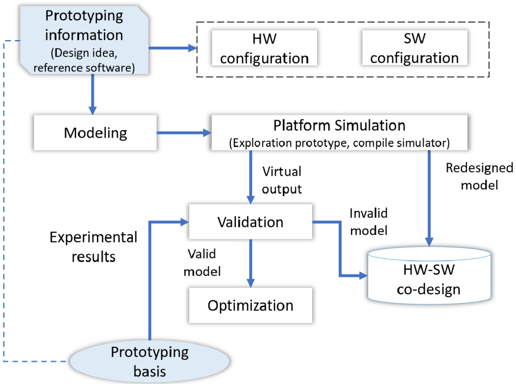

FIGURE 3. VP for validation and HW-SW co-design.

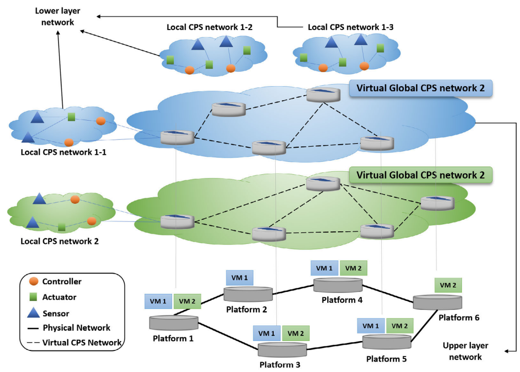

FIGURE 4. Network virtualization and their corresponding mapping to the system architecture [40].

the SoC design and verification to the electronic system level (ESL).

C. VIRTUAL PLATFORMS FOR CYBER-PHYSICAL CONFIGURATION AND NETWORKS

Other than focusing on SoCs and embedded applications, there have been a few virtual platforms that facilitate explorations of the overall system framework and network architecture. Ahn et al. [40] introduced a virtual platform named *Xebra*, targeting the need for a global-scale cyber-physical system by virtualizing the framework and isolation techniques that include CPS middleware. Their platform is unique in the sense that it allows the coexistence of various global-scale IoT solutions on a physical network through virtualization. To support the network among various CPS applications, they implemented low-overhead message control by managing a layered virtual network. The network virtualization and its corresponding mapping to the system architecture are depicted in Fig. 4.

Soares et al. [41] introduced a virtual platform for cloud-based network virtualization that is called Cloud4NFV. The platform is focused on Virtual Network Functions (VNFs) that follow the network architecture guidelines and aim to deliver a new service to end customers, emphasizing customer premises equipment (CPE) related functions. Furthermore, some other works have focused on the virtualization of specific network features, *e.g.*, Network Functions Virtualization (NFV) enhanced with Software Defined Networking (SDN) [42] and virtualized routing functions [43]. Necessary network functions like load balancing, routing, and firewall security are all performed by an NFV-based virtual framework instead of the hardware components. These studies have demonstrated that the potential benefits of NFV are expected to be substantial. Virtualization of network functions on general-purpose standardized hardware is projected to minimize capital and operational costs, as well as the time it takes to launch new services and products.

IV. DIGITAL TWINS

The concept of *digital twin* (DT) [44] has gained significant popularity for building advanced cyber-physical systems, smart systems, and IoT-infused applications. The idea was conceptualized by Grieves [45] as the conceptual paradigm underlying product lifecycle management. Unlike virtual platforms, digital twins focus on the physical behavior of the physical entity rather than abstracting any software layer. They offer several benefits, like simulation, prediction, and monitoring, once they combine the physical and virtual assets through the Internet-of-Things. Many important industries, including the manufacturing sector, connected and autonomous vehicles, healthcare, energy, city planning, and many more, are being revolutionized by DT technologies [46].

A. DEFINITIONS AND RELATION WITH IoT APPLICATIONS

DTs are defined as virtual prototypes or computer-based models that simulate, emulate, mirror, or "twin" the life of a physical entity, which could be an object or process [47]. DTs are not limited to just simulations or virtual models [48]. It is an intelligent, evolving digital counterpart of a physical entity that follows the life cycle of its physical counterpart to monitor and process various functions. Table-1 depicts the digital twin definition from three different perspectives. The first type emphasized the mirroring or virtual representation of a physical object or process. This definition, however, ignores any automated data or simulation perspective on that process. The second definition type focused on mainly portraying the DT as a simulation process, automated data, or prediction model. According to this definition, the data flow between DT and the physical entity is unidirectional *i.e.*, any change in the physical object will affect the virtual one, but not the other way around [49]. DT is defined as an integration process in the third type of definition. Here, DT incorporates both the physical object and its corresponding virtual model and continually adapts based on the connection between these two.

For the improvement of the IoT system in every aspect, DT can be constructed from any physical entity that can provide feedback based on simulation results. As discussed in Section II, virtual prototyping *i.e.*, DT for this discussion, can help develop the IoT application in terms of exploration, optimization, and security aspects. Fig. 5 depicts the

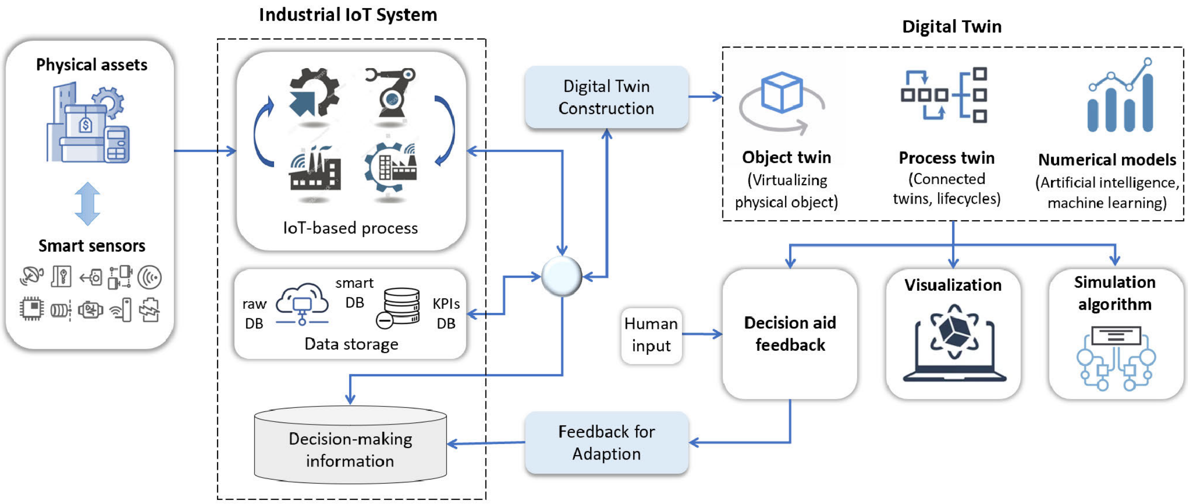

FIGURE 5. Digital twin construction for industrial IoT systems.

TABLE 1. Digital twin definitions.

Domain	Definition	Ref.
Digital counterpart, Model, Twin	The virtual and computerized counterpart of a physical system.	[50]
	DT is a virtual representation of a physical product or process, used to understand and predict its physical counterpart's performance characteristics.	[51]
	A dynamic digital representation of a physical system.	[52]
Simulation, Prediction	A simulation based on expert knowledge and real data collected from the existing system.	[53]
	Digital twin is to develop the virtual models for physical objects in order to simulate their behaviors	[54]
	Re-engineering computational model of structural life prediction and management.	[55]
Integration	Comprehensive physical and functional description of a component, product, or system together with available operational data.	[56]
	Integrated multi-physics, multi-scale, and probabilistic simulation compost or physical products, virtual products, data, services, and connections between them.	[57], [58]

construction of DT from a typical industrial IoT that is showing feedback for adaptation and also different kinds of DT models that can be involved. A typical industrial IoT system contains an IoT-based process, data storage, and decision-making system integrated with DT information flow. Here, DT computation modules process the virtual data after proper visualization and simulation along with human inputs if necessary and notify back to the physical system about the findings from the simulation to make necessary changes in the physical version or adapt system parameters if necessary [10].

B. AI AND ML-BASED NUMERICAL MODELS

Smart data analysis for IoT-based systems using artificial intelligence (AI) and machine learning (ML) has great potential in the context of prototyping with the digital twin. We mentioned the DT definition as an integrated system; the numerical model-based frameworks contribute to this purpose. Smart systems include various IoT devices that expedite real-time data processing *i.e.*, leading to the development of digital twins integrated with AI-ML techniques. As a result, methods like Generative Adversarial Networks (GANs) [59] and Restricted Boltzmann Machines (RBM) [60] are having a great impact on improving data quality and understanding time series with digital twin [61]. In some industries, the DT framework combines IoT, data analysis, and machine learning for prediction, monitoring, correction, and comparison activities to improve and control the existing IoT components. While developing complex cyber-physical systems, trial versions seem too expensive to deploy, especially in developing countries. In order to accurately predict the outcome of any system in advance, specific simulators are often used that are designed to replicate the physical system. These simulators are usually developed based on independent computational models *ie.* artificial intelligence concepts that require self-configuring data. This is where the DT can be of great potential, as the goal of a virtual model within a DT is to self-learn the data pattern in order to optimize the configuration of a physical system in real-time [62].

DT technology refers to the supervised and unsupervised learning algorithms that refine their predictive ability as they process continuously acquired sensed data from the physical twin and the surrounding environment [47]. Here, the virtual twin acts as an intelligent representation of the cognitive brain that performs a set of tasks via predictive algorithms. Feature selection and feature extraction methods play an important role in big data by reducing the data range and extracting only the informative data *i.e.*, enabling effective real-time system synchronization. Key AI-ML algorithms like pattern recognition, unsupervised and supervised learning, and statistical applications let the DT characterize, analyze, cluster, and classify input data from the surrounding CPS environment [63]. Analyzing data enables the detection of changes as well as the identification of relevant patterns and trends. Thus, various businesses are setting up new efficiencies as AI-powered digital agents can predict impending asset failure and the underlying causes weeks in advance. Industrial organizations can then use digital twins to propose process actions to maintain equipment health and reduce plant downtime.

Dröder et al. [64] proposed a machine learning-based digital twin for human-robot collaboration to eliminate the problem of safe movement of the robot in an unstructured human environment. To develop and test their approach, they developed a digital twin using MATLAB that is also extended by integrating with artificial neural networks (ANNs) [65]. A production system-based IoT framework for a digital twin combining machine learning and simulation is presented in another paper [66]. They used finite element method (FEM) simulation for the digital twin and adapted it with machine learning-based surrogate modeling of the FEM. Zhou et al. [67] presented an AI-based detection model for small objects via digital twin, aiming to dynamically synchronize a physical system with its virtual representation. For a smart manufacturing framework, they built their DT based on three parameters *i.e.*, product, operator, and equipment, establishing the infrastructure for real-time changes and realizing dynamic characteristics. The authors used a hybrid deep neural network model based on the combination of MobileNetv2, YOLOv4, and OpenPose to further develop the learning algorithm to realize efficient multi-type small object detection.

C. OBJECT AND PROCESS TWINNING

The digital twin is the most widely used virtual prototyping technology that acts as a bridge for integration between the physical and virtual components in terms of *object* and *process twinning*. More importantly, as the digitalization of industrial IoT becomes the foundation of smart manufacturing, DT is regarded as the biggest emerging technology trend and the most promising prototyping approach for realizing real-time object and process monitoring and maintenance in the industry. The digital twinning of objects aims at offering virtual counterparts of objects with real-time automated monitoring that takes part in automatic cyber-physical systems, while the digital twinning of a process virtualizes the whole CPS sub-system. Fig, 6 shows the concept of object and process twinning from CPS to DT.

So far, object twinning has been driven by the concept of physics-based modeling methods that entail observing and understanding a physical phenomenon of the object, converting the comprehension into mathematical equations, and finally exploring them. Rasheed et al. [61], discussed several multi-physical simulation and physical realism approaches

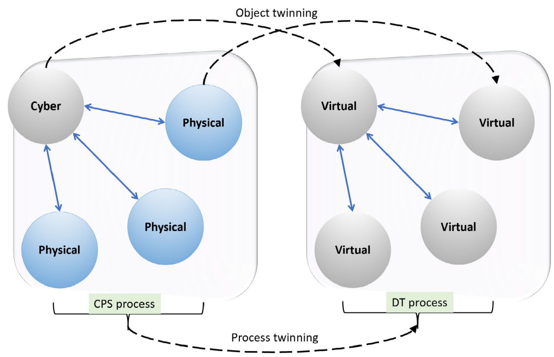

FIGURE 6. Object and process twinning from CPS to DT.

e.g., Finite Difference Method (FDM), Finite Element Method (FEM), Finite Volume Method (FVM), and Discrete Element Method (DEM). Wu et al. [49] discussed in detail on physical object twinning, enabling technology for modeling, physical data processing, and network coordination among the physical and virtual twins in terms of network topology. More depictions of object twinning aimed at structural prediction and crack tip insights can be found mostly in the aviation domain (*e.g.*, [68], [69]).

The process twining essentially includes the objects or components any process or system contains, though several DT structures do not necessarily virtualize the components *i.e.*, they use an abstract form of each component and focus more on the sub-system computation. Alam and El Saddik [8], introduced a digital twin architecture reference model for the cloud-based CPS, referred to as *C2PS*, where they analytically describe the key properties of their DT framework. *C2PS* allows exploring how the IoT sub-system can generate heterogeneous systems. They also validated the efficacy of their model by demonstrating a prototype driving assistance model for vehicular applications. Bao et al. [70] developed a DT architecture for the manufacturing sector that divides the DT into three components: product, process, and operation, each of which has a distinct architecture.

V. ENABLING TECHNOLOGIES FOR PROTOTYPING

Several enabling technologies are critical in building an intelligent virtual representation of a physical entity and supporting a continuous two-way feedback loop between the entities. In this section, we'll go through some of the most notable enabling technologies that researchers have used to develop VPS, DTs, or any virtualization frameworks to meet their needs.

A. MODELING AND SIMULATION

Virtual prototyping frameworks for intelligent systems can be perceived as just another name for "simulation of your system design". The term "modeling and simulation" can refer to a wide range of frameworks and software components that can be used to direct developers in creating a critical component of a virtual representation of a physical object [71]. Therefore, modeling and simulation are key elements in building a virtual prototype. So, the question arises, "why use fancy names like digital twins and virtual platforms?" Although virtual prototypes and simulation both employ digital models to imitate items and processes, there are some significant differences between the two. If we look at the digital twin as an illustrative example — the most noteworthy aspect is that a digital twin develops a virtual environment capable of studying various simulations, backed by real-time data and a two-way communication channel between the sensor-equipped twin and the twin that collects the data. As a result, predictive analytical models become more accurate, providing better management and monitoring of products, regulations, and procedures [72].

The key differences between a virtual prototype and a simulation model can be seen in terms of the following categories.

- Static vs. Active: A simulation model is static since it does not evolve unless the designer adds new components. While a digital twin will initially start off quite similar to a simulation model, the addition of real-time data allows the twin to alter and grow to provide a more active simulation [73]. A digital twin can develop over the course of a product lifecycle as more data is gathered and analyzed, providing unique comprehension that is not possible with a static simulation [74].
- The present: Simulations, at best, can assist in understanding what may occur in the real world. Digital twins help understand not only what might happen, but also what is happening [75].
- Application: A simulation is useful for product design because it enables designers to test various scenarios against predetermined criteria. The uses of a digital twin, however, are not restricted to specific business workflow areas because its scope is much broader and encompasses all stages of a product lifecycle.

With these distinctions in mind, a virtual prototype is developed from various modeling methodologies that provide the prototyping platform with the initial cyber backbone. From Fig. 2, we understand that VPs are traditionally developed using functional TLM models, system C, and OVP emulators *i.e.*, building an abstraction level through these aforementioned modeling methodologies. The "Programmers' View" (PV) level of abstraction consists of the register accurate transaction-level models (TLMs) of the peripherals and the instruction-set simulator (ISS) of the CPU [76]. The fundamental element of the TLM modeling approach is the distinction between the communication layer, functionality, and architectural elements as represented by time and power [77], [78].

In the case of digital twins, the modeling techniques are not specifically defined, as it is considered an interdisciplinary and versatile technology that varies by definition as well. Nonetheless, several researchers developed their own methods of modeling DT frameworks and attempted to establish it as an abstractly organized architecture. A group of authors [79], [80] established the modeling basis of the DT based on two components: a virtual twin of the physical entity and an API. They demonstrated the usage of API as a middleware that allows the DT to connect with external systems. Another research study explored the modeling techniques such as Design Elements, 8D-Model, and V-IoT to develop DT for smart factories [81]. In general, DTs are modeled from the characteristics of the target physical entity, and simulations are run based on the real-time behavioral data provided.

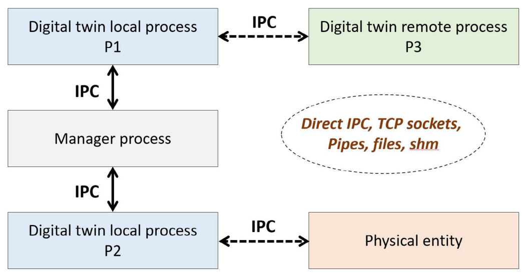

FIGURE 7. Inter-process communication (IPC) among digital twin processes.

B. COMMUNICATIONS

One of the essential components of a virtual prototype is the communication framework that allows the physical and virtual entities to coexist. Additionally, the communication among the computation processes within a virtual prototype is crucial for the overall functionality of the cyber-physical system. To exchange data and information, the cooperating processes in a prototyping framework must communicate with one another. The mechanism for communicating between these processes is known as inter-process communication (IPC) [82]. The two modes of IPC are — shared memory and message passing.

Virtual prototyping technologies employ various kinds of IPC to establish communication in the virtual environment within those two IPC modes. Threads can now transcend process boundaries thanks to the OS feature known as "direct IPC," [83] which repurposes and expands the CODOMs [84] design. The OS kernel is removed from the critical inter-process communication path, and processes are mapped into a shared address space. Another useful communication feature is socket programming based on the client-server model [85]. These include various types of sockets, *e.g.*, Transmission Control Protocol (TCP) [86], User Datagram Protocol (UDP), and raw sockets.

C. IoT CONCEPTS

IoT envisions a world in which everything is intelligently connected, invoking technologies such as wireless sensor networks, digital twins, machine learning, edge computing, cloud computing, and many more within the context of distributed systems. The primary IoT concepts tell us about

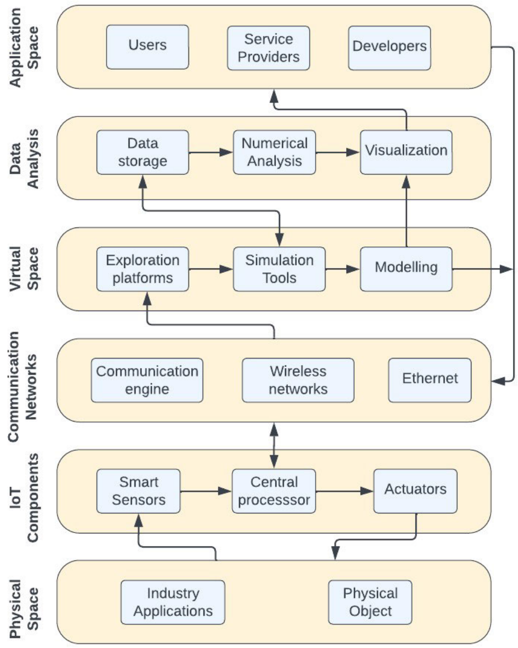

FIGURE 8. Prototyping Conceptual framework within the Context of Internet-of-Things.

sensors, actuators, and controllers/systems embedded within the enabling technology. Modern virtual prototypes are often built based on this IoT concept, with the computational processes functioning as sensors, actuators, or controllers. IoT sensors (*i.e.*, smart sensors) play a crucial role in sending real-time data to the virtual environment, allowing structural simulations. The depth of heterogeneous data that IoT sensors provide can be utilized to virtualize and visualize various industrial applications, enabling the prevention of risks and the remote management of workplace safety issues [87]. Fig. 8 shows a generic conceptual framework for prototyping derived from various models proposed by academia and industry. Following an architectural study of some of the existing concepts, a set of layering principles and functionality is presented.

Edge and cloud computing are often used to move IoT sensory data across edge systems and public clouds. The virtualization of composite heterogeneous IoT systems always requires heavy processing, calling for the need for distributed computing. Jiang et al. [88] built a DT based on a traditional IoT framework that employs both edge and cloud computing, splitting the framework into two parts. Cloud platforms are more common for building virtual prototypes that take care of heavy computations while the prototyping framework synchronizes IoT-related functions between the physical and virtual entities [89], [90].

D. VIRTUAL AND AUGMENTED REALITY

Other than just computational and simulation-based models, prototypes are also constructed in a more visualized and immersive manner with the help of virtual reality (VR) and augmented reality (AR) technologies. VR is often used to navigate, interact with, and explore the virtual environment realistically, just like they would with the actual equipment. Users can learn about a certain physical entity immersively with a VR-based virtual environment without even interrupting the actual entity itself [91], [92]. AR helps to bring a virtual prototyping component into the real environment by establishing on-demand live synchronization and integration. It can speed up access to virtual environment interfaces by overlaying virtual data and images on the camera feed while the camera is directed at the physical twin itself [93]. Microsoft HoloLens is widely used to visualize the AR components as part of the DT data in a real industrial environment [94].

Although both technologies have individually been crucial catalysts for prototyping activities, neither is sufficient on its own. Functionalities like two-way communications, real-time synchronization of virtual prototypes, and human-machine interfaces enable the virtual framework to achieve critical challenges. Having said that, some studies [95], [96] have combined both VR and AR technologies to achieve this goal, resulting in more efficient real-time simulation.

VI. MODERN VIRTUAL PROTOTYPING IN CURRENT INDUSTRY

Apart from the definition and application of *virtual platform* and *digital twin* discussed above, there has been some research on developing unique virtual prototypes that take inspiration from both virtual platforms as well as digital twins and focus on prototyping solutions for their respective domains. In this section, we present different virtual prototyping approaches for some representative industry applications *i.e.*, energy, manufacturing, vehicular, healthcare, and agriculture. A comprehensive overview of the prototyping applications for various IoT-based industries is portrayed in Fig. 9.

A. ENERGY

Smart grids constitute one of the key applications of IoT technology in the energy sector. A fully operational smart grid integrates complex cyber systems and physical network infrastructure that includes communication and information technologies. Assessing the resiliency of the grid and mitigation strategy of critical cases, the concept of virtual replicas has been proven as a useful approach in some research. From that perspective, Joseph et al. [97] proposed a virtual prototype of a power system that can analytically model and predict the fault-induced dynamic voltage recovery (FIDVR) event. The virtual replica consists of a dynamic mitigation strategy that can solve the mitigation goal while serving faster than a real-time replica, causing a minimal level of undervoltage load shedding. A cloud-based virtual smart grid architecture has been introduced in a paper [98], that virtualizes the smart grid's integrated array of sensory, communication, and control systems, and integrates the grid network with cloud resources. The goal is to utilize this cloud-based

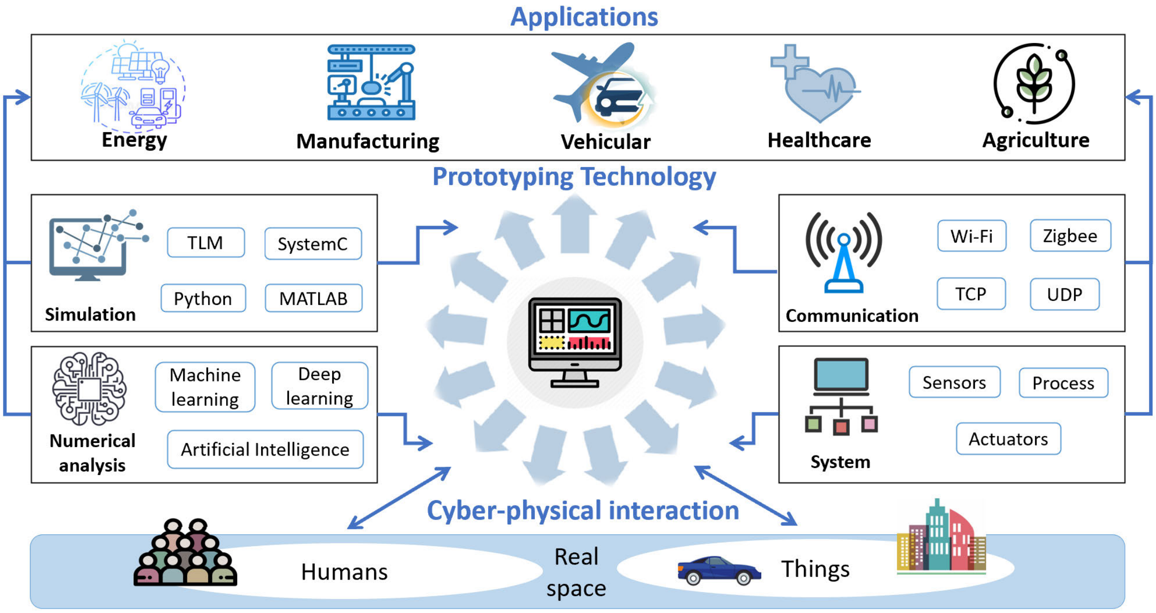

FIGURE 9. Virtual prototyping application in various industrial IoT applications.

virtual platform for faster and wider distribution of smart grid applications with economies of scale while maintaining the quality of service (QoS).

Another unique online DT framework is introduced by Zhou et al. [94], which enables real-time online power grid analysis. Their primary goal was to minimize the overall online analysis response time (*i.e.*, from 10 minutes to less than a minute) for a more feasible and practical virtual prototype-based application. In the context of microgrid security, Danilczyk et al. [99], [100] proposed a novel digital twin framework *ANGEL*, to potentially improve the security and resiliency of the microgrid. *ANGEL* will be able to model the microgrid's cyber and physical layers and provide real-time data visualization, minimizing component failures as well as the effects of cyberattacks. To prevent microgrid cyber attacks, another research [101] established an IoT-based DT that covers more ranges of attack resiliency *e.g.*denial of service (DoS), fault injection, etc.

B. MANUFACTURING

The manufacturing, automation, and process industries have been exploiting the use of virtual prototyping (mostly as digital twins) for quite a decade without openly mentioning it. However, with the current trend of virtualizing industrial IoT components for seamless exploration and the demand for high-quality products efficiently, the manufacturing industries are adapting and developing more virtual architectures for their respective system designs. Among them, Tao et al. [57], introduced a novel virtual prototyping concept called Digital Twin Shopfloor (DTS) and discussed its four key components *i.e.*, physical shop-floor, virtual shop-floor, shop-floor service system, and shop-floor digital twin data. They proposed an effective way to find convergence between the physical and virtual worlds for an efficient production process. Further applications of DTS have been explored as well in a few more studies [102], [103]. Another interesting work has been proposed by Gehrmann and El Saddik [104], where they discussed how a digital twin replication model and associated security architecture can be utilized to facilitate data exchange and control of security-critical procedures. They provided a strong foundation for further security-driven research on improving the overall industrial automation domain with the efficient use of an intelligent digital twin framework. Cyber-Physical Cloud Manufacturing (CPCM) systems [105] took on a new shape with the adaption of virtual machine technology, which includes multiple physical machines and cloud servers, with the cloud servers acting as a hub for all applications gathering data. Nguyen et al. [106] proposed such a model that can be coherently adapted to the CPCM platform to implement a real-scaled virtual system and minimize the consumption of the physical resources in the system, all while ensuring real-time communication between operators and industrial machines. An overview of prototyping architecture used typically for manufacturing systems is shown in Fig 10.

In the context of Industry 4.0, Vachálek et al. [19], presented a digital twin simulation model as an augmented manufacturing project based on the plant simulation tool provided by SIEMENS. The authors aimed to further establish the concept of Industry 4.0 for the need for efficient augmented production strategies using a novel virtual model. To evaluate factory design and avoid design flows, Guo et al. [107], proposed a flexible digital replica of their design for smart manufacturing. Conventional factory designs typically include three primary design stages *i.e.*, conceptual design, elaborate design, and finalized design, in which the virtual model

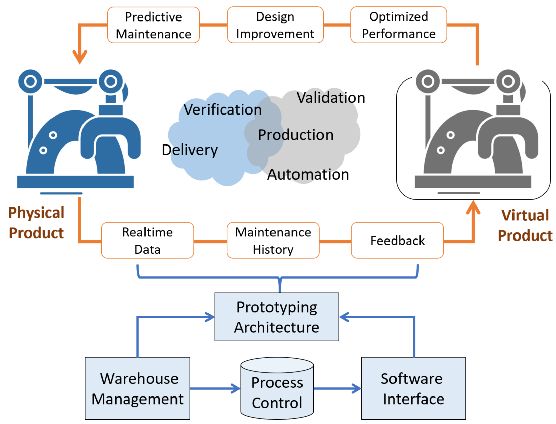

FIGURE 10. **An overview of prototyping framework for Industry 4.0 smart manufacturing.**

emulates various manufacturing strategies and debug decisions by connecting with multiple system software like PLC (programmable logic controller) and MES (manufacture execution system). Another group of authors presented an intelligent virtual framework for smart manufacturing with industrial CPS, where environmental parameters like operators, equipment, and products are virtualized for real-time changes in the manufacturing workshop [67]. A couple of studies by Uhlemann et al. [108], [109] provided a multi-modal data acquisition system that realized a cyber-physical production system in order to minimize the delay between the time of data acquisition and the development of the prototyping framework.

C. VEHICULAR SYSTEMS

Nowadays, the virtualization of vehicular components has become a viable topic to explore the possibilities of development in vehicular electronics. Notable vehicular applications, *e.g.*, aviation and automotive industries, are developing rapidly in terms of novel IoT-based concepts. In the aviation industry, virtualization technology is primarily used for predictive maintenance, *e.g.*, identifying dangerous changes in structural aircraft and then activating optimization and diagnostic mechanisms. Yang et al. [69] modeled a digital twin of the aircraft to figure out any crack growth information of the aircraft material (*e.g.*, steel and aluminum alloys). The modeled DT allows exploiting an automatic image tracking method to predict the crack growth mechanisms during the whole aircraft life-cycle, which can help reduce development costs. Another work by Majumdar et al. [68] depicts a DT model to analyze microstructural changes due to the surrounding environment that may impact the structural performance of the aircraft. A dynamic Bayesian network based on the digital twin was introduced to monitor the crack growth situation of aircraft *i.e.*, control the health state of aircraft wings [110]. Another aircraft health monitoring DT [111] focuses on modeling the aircraft tire at touchdown. They aimed to accurately predict tire-touchdown wear to avoid critical tire-related accidents during landing, which might increase costs, and cause logistical complexity.

There are very few closely depicted virtualization works to mention in the automotive industry. Among them, Strobl et al. [112] provided a thorough discussion of the advantages of automotive virtualization as a foundation for consolidating a wide range of ECUs into a few Domain Controller Units (DCUs). Safar et al. [113] added a VP to the V-model of automotive software development as part of an improved methodology that allows SoC, ECU, and system-level verification and validation. It also includes the AUTOSAR software's fault injection capability and co-debugging mechanism. Lee et al. [114] proposed a Virtualized Automotive Display System capable of managing various execution domains such as automotive control software and in-vehicle infotainment (IVI) software. In the field of connected and autonomous vehicles, some studies [115], [116] have shown how car manufacturers employ connecting vehicles to their digital twins to retrieve functional data about the vehicle and support preventive and emergency maintenance of their vehicles. Recent work by Kabir et al. [117], [118], shows a virtual prototyping infrastructure called ViVE for the modeling and simulation of vehicular electronics. Unlike other automotive simulation platforms, ViVE distinguishes itself by enabling the extension of new use cases, the exploration of inter-component and system interactions, and the exercise of optimization and security targets.

D. HEALTHCARE

With the evolution of IoT infrastructure in the healthcare domain, virtual prototyping technology has been proven to be extremely beneficial in intelligent human body monitoring and the maintenance of medical devices. Although the medical field aims to utilize this technology mostly to build a virtual human body, our discussion focuses on the IoT component of this domain *i.e.*, medical devices and hospital lifecycle. Liu et al. [119] proposed a novel and extendable framework of the cloud healthcare system based on digital twin healthcare (CloudDTH) for monitoring, predicting, and diagnosing various health aspects of elderly patients using *e.g.*, wearable medical devices. The authors aim to achieve interaction and coordination between physical and virtual entities in the medical domain. Accordingly, they explored enabling technology with their model and demonstrated its feasibility via a case study for real-time supervision.

In the context of remote surgery, Laaki et al. [120] developed a novel digital prototype to analyze the requirements of mobile network communication to support surgery remotely. The authors addressed the cybersecurity of the system (comprised of a robotic arm and virtual reality (VR) over a 4G mobile network), by incorporating and studying a network manipulation module within the digital twin framework. Another work also described the virtualization of medicine with the adoption of Wireless Body Area Networks (WBAN) based on IoT along with cloud computing systems, providing more definitions of Medical Cyber-Physical Systems (MCPSs) [121], [122]. Kocabas et al. [123] provided a comprehensive discussion of such MCPSs that includes the integration of modeling, data acquisition, cloud storage, and actuators. This development of new virtualization methodologies has been crucial for monitoring and treating patients with critical conditions. Prototyping using AR/VR technologies also have become popular for automated remote health monitoring of patients using smart sensors [124], [125].

E. AGRICULTURE

The agriculture domain is taking on a new shape by exploiting advances in IoT for crop monitoring, agro-technology, technical resources for farming, and smart plant development systems. In other words, crop monitoring and development are becoming part of smart cyber-physical systems, as they combine the capabilities of IoT components *e.g.*, sensory data collection, cloud service, and managing machinery. Skobelev et al. [126] introduced a multi-agent approach for developing digital twins of plants that enables the exploration of different plant development phases and forecasting of harvesting. Their work demonstrates how domain knowledge of new farming technologies for plant growth may be formalized and automated when precision agriculture technologies are introduced. In the context of smart farming, a virtual representation of a farm, based on the Internet-of-Things, was proposed in a paper [127], that can realize its surrounding environment by gathering adequate information from the farm. The virtual prototype further enhances the smart system associated with the farm to help the farmers better develop their smart farming system in terms of equipment and monitoring.

"Vertical farming" (VF) is a critical emergent concept. It tries to alleviate the burden on traditional agricultural land by farming upwards rather than outwards, and it's notably appealing for application in urban environments because it incorporates soil-free growing technologies [128]. In this area, Monteiro et al. [129] proposed a virtual prototyping model for sustainable agriculture that aims to create a joint structure of IoT-enabled systems involving physical and virtual layers for vertical farming. Ultimately, developing a digital twin model for vertical farming was their primary objective that achieves several outcomes like operation, monitoring, and optimization of the smart agro-food life-cycle. Smart Agriculture found a promising direction with the proposal of Angin et. al [130], where a digital twin framework *AgriLoRa* has been discussed to address the issue of growing high-yield crop production needs around the world. This framework comprises a farmland-based wireless sensor network and cloud-based computer vision algorithms for detecting plant diseases, weed groups, and nutrient deficits.

VII. CONCLUSION

The Internet-of-Things is ushering in a confluence of many disciplines, including artificial intelligence, computing system design, and smart industrial infrastructure. In the past decade, virtual prototyping solutions for various IoT applications have advanced in the form of virtual platforms, digital twins, a blend of both, and concepts not analogous to either. We presented a comprehensive high-level overview of virtual prototyping solutions in IoT applications. We discussed how this technology has proven beneficial in three key aspects *i.e.*, system exploration, optimization, and security. The paper has addressed and disambiguated three critical issues: (1) the definitions and types of various virtual prototyping techniques in industrial IoT; (2) the characteristics of various prototyping solutions in terms of modeling, simulation, and application; and (3) the application of virtual prototyping in the modern IoT industry. We believe that the overview will pave the way for a comprehensive understanding of the state of the art in this area and facilitate future research. In particular, novel architectural concepts are being developed, especially in the area of digital twins. Therefore, robust and hybrid forms of virtualization are combining various modeling approaches that can become more appealing to the development of more intelligent, secure, and autonomous systems.

REFERENCES

[1] E. A. Kosmatos, N. D. Tselikas, and A. C. Boucouvalas, "Integrating RFIDs and smart objects into a Unified Internet of Things architecture," *Adv. Internet Things*, vol. 1, no. 1, pp. 5–12, 2011.

[2] J. Hu, B. Lennox, and F. Arvin, "Robust formation control for networked robotic systems using negative imaginary dynamics," *Automatica*, vol. 140, Jun. 2022, Art. no. 110235.

[3] Q. Shafi, "Cyber physical systems security: A brief survey," in *Proc. 12th Int. Conf. Comput. Sci. Appl.*, Jun. 2012, pp. 146–150.

[4] R. Poovendran, "Cyber–physical systems: Close encounters between two parallel worlds [point of view]," *Proc. IEEE*, vol. 98, no. 8, pp. 1363–1366, Aug. 2010.

[5] K. Shafique, B. A. Khawaja, F. Sabir, S. Qazi, and M. Mustaqim, "Internet of Things (IoT) for next-generation smart systems: A review of current challenges, future trends and prospects for emerging 5G-IoT scenarios," *IEEE Access*, vol. 8, pp. 23022–23040, 2020.

[6] H. Boyes, B. Hallaq, J. Cunningham, and T. Watson, "The industrial Internet of Things (IIoT): An analysis framework," *Comput. Ind.*, vol. 101, pp. 1–12, Oct. 2018.

[7] W. Mueller, M. Becker, A. Elfeky, and A. DiPasquale, "Virtual prototyping of cyber-physical systems," in *Proc. 17th Asia South Pacific Design Autom. Conf.*, Jan. 2012, pp. 219–226.

[8] K. M. Alam and A. El Saddik, "C2PS: A digital twin architecture reference model for the cloud-based cyber-physical systems," *IEEE Access*, vol. 5, pp. 2050–2062, 2017.

[9] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for industry 4.0-based manufacturing systems," *Manuf. Lett.*, vol. 3, pp. 18–23, Jan. 2015.

[10] D. Y. Jia, K. Lu, J. Wang, X. Zhang, and X. Shen, "A survey on platoon-based vehicular cyber-physical systems," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 1, pp. 263–284, Mar. 2016.

[11] Y. Xu, Y. Sun, J. Wan, X. Liu, and Z. Song, "Industrial big data for fault diagnosis: Taxonomy, review, and applications," *IEEE Access*, vol. 5, pp. 17368–17380, 2017.

[12] T. Catarci, D. Firmani, F. Leotta, F. Mandreoli, M. Mecella, and F. Sapio, "A conceptual architecture and model for smart manufacturing relying on service-based digital twins," in *Proc. IEEE Int. Conf. Web Services (ICWS)*, Jul. 2019, pp. 229–236.

[13] Y. Zhou, L. Tian, C. Zhu, X. Jin, and Y. Sun, "Video coding optimization for virtual reality 360-degree source," *IEEE J. Sel. Topics Signal Process.*, vol. 14, no. 1, pp. 118–129, Jan. 2020.

[14] T. Schuster, R. Meyer, R. Buchty, L. Fossati, and M. Berekovic, "SoCRocket—A virtual platform for the European Space Agency's SoC development," in *Proc. 9th Int. Symp. Reconfigurable Communication-Centric Systems-on-Chip (ReCoSoC)*, May 2014, pp. 1–7.

[15] T.-C. Yeh, Z.-Y. Lin, and M.-C. Chiang, "Optimizing the simulation speed of QEMU and SystemC-based virtual platform," in *Proc. 2nd Int. Conf. Inf. Eng. Comput. Sci.*, Dec. 2010, pp. 1–4.
[16] H. Hawilo, M. Jammal, and A. Shami, "Orchestrating network function virtualization platform: Migration or re-instantiation?" in *Proc. IEEE 6th Int. Conf. Cloud Netw. (CloudNet)*, Sep. 2017, pp. 1–6.
[17] L. Wang, Z. Lu, X. Wen, R. Knopp, and R. Gupta, "Joint optimization of service function chaining and resource allocation in network function virtualization," *IEEE Access*, vol. 4, pp. 8084–8094, 2016.
[18] S. M. Jeon and S. Schuesslbauer, "Digital twin application for production optimization," in *Proc. IEEE Int. Conf. Ind. Eng. Eng. Manage. (IEEM)*, Dec. 2020, pp. 542–545.
[19] J. Vachalek, L. Bartalsky, O. Rovny, D. Sismisova, M. Morhac, and M. Loksik, "The digital twin of an industrial production line within the industry 4.0 concept," in *Proc. 21st Int. Conf. Process Control (PC)*, Jun. 2017, pp. 258–262.
[20] N. Stojanovic and D. Milenovic, "Data-driven digital twin approach for process optimization: An industry use case," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Dec. 2018, pp. 4202–4211.
[21] S. Karnouskos, "Stuxnet worm impact on industrial cyber-physical system security," in *Proc. 37th Annu. Conf. IEEE Ind. Electron. Soc.*, Nov. 2011, pp. 4490–4494.
[22] H. He, C. Maple, T. Watson, A. Tiwari, J. Mehnen, Y. Jin, and B. Gabrys, "The security challenges in the IoT enabled cyber-physical systems and opportunities for evolutionary computing & other computational intelligence," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jul. 2016, pp. 1015–1021.
[23] T. Kulik, C. Gomes, H. D. Macedo, S. Hallerstede, and P. G. Larsen, "Towards secure digital twins," in *Leveraging Applications of Formal Methods, Verification and Validation. Practice*. Rhodes, Greece: Springer, Oct. 2022, pp. 159–176.
[24] S. Almeaibed, S. Al-Rubaye, A. Tsourdos, and N. P. Avdelidis, "Digital twin analysis to promote safety and security in autonomous vehicles," *IEEE Commun. Standards Mag.*, vol. 5, no. 1, pp. 40–46, Mar. 2021.
[25] C. Alcaraz and J. Lopez, "Digital twin: A comprehensive survey of security threats," *IEEE Commun. Surveys Tuts.*, vol. 24, no. 3, pp. 1475–1503, 3rd Quart., 2022.
[26] X. Lou, Y. Guo, Y. Gao, K. Waedt, and M. Parekh, "An idea of using digital twin to perform the functional safety and cybersecurity analysis," in *INFORMATIK 2019: 50 Jahre Gesellschaft für Informatik–Informatik für Gesellschaft (Workshop-Beiträge)*, 2019, Bonn, Germany: Gesellschaft für Informatik eV, 2019.
[27] S. Ahn and S. Malik, "Automated firmware testing using firmware-hardware interaction patterns," in *Proc. Int. Conf. Hardw./Softw. Codesign Syst. Synth.*, Oct. 2014, p. 25.
[28] R. Kannavara, C. J. Havlicek, B. Chen, M. R. Tuttle, K. Cong, S. Ray, and F. Xie, "Challenges and opportunities with concolic testing," in *Proc. Nat. Aerosp. Electron. Conf. (NAECON)*, Jun. 2015, pp. 374–378.
[29] R. Leupers, F. Schirrmeister, G. Martin, T. Kogel, R. Plyaskin, A. Herkersdorf, and M. Vaupel, "Virtual platforms: Breaking new grounds," in *Proc. Design, Autom. Test Eur. Conf. Exhib. (DATE)*, Mar. 2012, pp. 685–690.
[30] K. Lu, D. Müller-Gritschneder, and U. Schlichtmann, "Accurately timed transaction level models for virtual prototyping at high abstraction level," in *Proc. Design, Autom. Test Eur. Conf. Exhib. (DATE)*, Mar. 2012, pp. 135–140.
[31] A. Biondi, D. Casini, G. Cicero, N. Borgioli, G. Buttazzo, G. Patti, L. Leonardi, L. L. Bello, M. Solieri, P. Burgio, I. S. Olmedo, A. Ruocco, L. Palazzi, M. Bertogna, A. Cilardo, N. Mazzocca, and A. Mazzeo, "SPHERE: A multi-SoC architecture for next-generation cyber-physical systems based on heterogeneous platforms," *IEEE Access*, vol. 9, pp. 75446–75459, 2021.
[32] S. Hong, S. Yoo, S. Lee, S. Lee, H. J. Nam, B.-S. Yoo, J. Hwang, D. Song, J. Kim, J. Kim, H. Jin, K.-M. Choi, J.-T. Kong, and S. Eo, "Creation and utilization of a virtual platform for embedded software optimization: An industrial case study," in *Proc. 4th Int. Conf. Hardw./Softw. codesign Syst. Synth.*, Oct. 2006, pp. 235–240.
[33] Y.-L. Lin and A. W. Y. Su, "Functional verifications for SoC software/hardware co-design: From virtual platform to physical platform," in *Proc. IEEE Int. SOC Conf.*, Sep. 2011, pp. 201–206.
[34] M.-C. Chiang, T.-C. Yeh, and G.-F. Tseng, "A QEMU and SystemC-based cycle-accurate ISS for performance estimation on SoC development," *IEEE Trans. Comput.-Aided Design Integr. Circuits Syst.*, vol. 30, no. 4, pp. 593–606, Apr. 2011.
[35] F. Cucchetto, A. Lonardi, and G. Pravadelli, "A common architecture for co-simulation of SystemC models in QEMU and OVP virtual platforms," in *Proc. 22nd Int. Conf. Very Large Scale Integr. (VLSI-SoC)*, Oct. 2014, pp. 1–6.
[36] C.-S. Peng, L.-C. Chang, C.-H. Kuo, and B.-D. Liu, "Dual-core virtual platform with QEMU and SystemC," in *Proc. Int. Symp. Next Gener. Electron.*, Nov. 2010, pp. 69–72.
[37] G. Delbergue, M. Burton, F. Konrad, B. Le Gal, and C. Jego, "QBox: An industrial solution for virtual platform simulation using QEMU and SystemC TLM-2.0," in *Proc. 8th Eur. Congr. Embedded Real Time Softw. Syst. (ERTS)*, 2016, pp. 1–11.
[38] M. Vora, P. Mishra, and A. S. Kurhade, "Integration of pycachesim with QEMU," in *Proc. 4th Int. Conf. Recent Trends Comput. Sci. Technol. (ICRTCST)*, Feb. 2022, pp. 27–30.
[39] A. Wicaksana and C. M. Tang, "Virtual prototyping platform for multiprocessor system-on-chip hardware/software co-design and co-verification," in *Proc. Int. Conf. Comput. Inf. Sci.* Cham, Switzerland: Springer, 2017, pp. 93–108.
[40] S. Ahn, C. Yoo, S. Lee, H. Lee, and S. J. Kim, "Implementing virtual platform for global-scale cyber physical system networks," *Int. J. Commun. Syst.*, vol. 28, no. 13, pp. 1899–1920, Sep. 2015.
[41] J. Soares, M. Dias, J. Carapinha, B. Parreira, and S. Sargento, "Cloud4NFV: A platform for virtual network functions," in *Proc. IEEE 3rd Int. Conf. Cloud Netw. (CloudNet)*, Oct. 2014, pp. 288–293.
[42] G. Monteleone and P. Paglierani, "Session border controller virtualization towards 'service-defined' networks based on NFV and SDN," in *Proc. IEEE SDN Future Netw. Services (SDN4FNS)*, Nov. 2013, pp. 1–7.
[43] J. Batalle, J. Ferrer Riera, E. Escalona, and J. A. Garcia-Espin, "On the implementation of NFV over an OpenFlow infrastructure: Routing function virtualization," in *Proc. IEEE SDN Future Netw. Services (SDNFNS)*, Nov. 2013, pp. 1–6.
[44] D. J. Wagg, K. Worden, R. J. Barthorpe, and P. Gardner, "Digital twins: State-of-the-art and future directions for modeling and simulation in engineering dynamics applications," *J. Risk Uncertainty Eng. Syst., B, Mech. Eng.*, vol. 6, no. 3, Sep. 2020, Art. no. 030901.
[45] M. W. Grieves, "Virtually intelligent product systems: Digital and physical twins," Tech. Rep., 2019.
[46] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, and A. Y. C. Nee, "Enabling technologies and tools for digital twin," *J. Manuf. Syst.*, vol. 58, pp. 3–21, Jan. 2021.
[47] B. R. Barricelli, E. Casiraghi, and D. Fogli, "A survey on digital twin: Definitions, characteristics, applications, and design implications," *IEEE Access*, vol. 7, pp. 167653–167671, 2019.
[48] S. Boschert and R. Rosen, "Digital twin—The simulation aspect," in *Mechatronic Futures*. Cham, Switzerland: Springer, 2016, pp. 59–74.
[49] Y. Wu, K. Zhang, and Y. Zhang, "Digital twin networks: A survey," *IEEE Internet Things J.*, vol. 8, no. 18, pp. 13789–13804, Sep. 2021.
[50] E. Negri, L. Fumagalli, and M. Macchi, "A review of the roles of digital twin in CPS-based production systems," *Proc. Manuf.*, vol. 11, pp. 939–948, 2017.
[51] (2021). *Digital Twin: Siemens*. [Online]. Available: https://www.plm.automation.siemens.com/global/en/our-story/glossary/digital-twin/24465
[52] A. Madni, C. Madni, and S. Lucero, "Leveraging digital twin technology in model-based systems engineering," *Systems*, vol. 7, no. 1, p. 7, Jan. 2019.
[53] T. Gabor, L. Belzner, M. Kiermeier, M. T. Beck, and A. Neitz, "A simulation-based architecture for smart cyber-physical systems," in *Proc. IEEE Int. Conf. Autonomic Comput. (ICAC)*, Jul. 2016, pp. 374–379.
[54] Q. Qi and F. Tao, "Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison," *IEEE Access*, vol. 6, pp. 3585–3593, 2018.
[55] M. Grieves and J. Vickers, "Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems," in *Transdisciplinary Perspectives on Complex Systems*. Cham, Switzerland: Springer, 2017, pp. 85–113.
[56] S. Boschert, C. Heinrich, and R. Rosen, "Next generation digital twin," in *Proc. TMCE*, Las Palmas de Gran Canaria, Spain, 2018, pp. 7–11.
[57] F. Tao and M. Zhang, "Digital twin shop-floor: A new shop-floor paradigm towards smart manufacturing," *IEEE Access*, vol. 5, pp. 20418–20427, 2017.
[58] F. Tao, M. Zhang, Y. Liu, and A. Y. C. Nee, "Digital twin driven prognostics and health management for complex equipment," *CIRP Ann.*, vol. 67, no. 1, pp. 169–172, 2018.

[59] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks," *Commun. ACM*, vol. 63, no. 11, pp. 139–144, 2020.

[60] A. Fischer and C. Igel, "An introduction to restricted Boltzmann machines," in *Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications*. Buenos Aires, Argentina: Springer, Sep. 2012, pp. 14–36.

[61] A. Rasheed, O. San, and T. Kvamsdal, "Digital twin: Values, challenges and enablers from a modeling perspective," *IEEE Access*, vol. 8, pp. 21980–22012, 2020.

[62] H. X. Nguyen, R. Trestian, D. To, and M. Tatipamula, "Digital twin for 5G and beyond," *IEEE Commun. Mag.*, vol. 59, no. 2, pp. 10–15, Feb. 2021.

[63] K. Wärmefjord, R. Söderberg, L. Lindkvist, B. Lindau, and J. S. Carlson, "Inspection data to support a digital twin for geometry assurance," in *Proc. ASME Int. Mech. Eng. Congr. Expo.* New York, NY, USA: American Society of Mechanical Engineers, vol. 58356, 2017, p. 10.

[64] K. Dröder, P. Bobka, T. Germann, F. Gabriel, and F. Dietrich, "A machine learning-enhanced digital twin approach for human–robot-collaboration," *Proc. Cirp*, vol. 76, pp. 187–192, Jan. 2018.

[65] A. K. Jain, J. Mao, and K. M. Mohiuddin, "Artificial neural networks: A tutorial," *Computer*, vol. 29, no. 3, pp. 31–44, Mar. 1996.

[66] A. Hürkamp, S. Gellrich, T. Ossowski, J. Beuscher, S. Thiede, C. Herrmann, and K. Dröder, "Combining simulation and machine learning as digital twin for the manufacturing of overmolded thermoplastic composites," *J. Manuf. Mater. Process.*, vol. 4, no. 3, p. 92, 2020.

[67] X. Zhou, X. Xu, W. Liang, Z. Zeng, S. Shimizu, L. T. Yang, and Q. Jin, "Intelligent small object detection based on digital twinning for smart manufacturing in industrial CPS," *IEEE Trans. Ind. Informat.*, to be published.

[68] P. K. Majumdar, M. FaisalHaider, and K. Reifsnider, "Multi-physics response of structural composites and framework for modeling using material geometry," in *Proc. 54th AIAA/ASME/ASCE/AHS/ASC Struct., Structural Dyn., Mater. Conf.*, 2013, p. 1577.

[69] J. Yang, W. Zhang, and Y. Liu, "Subcycle fatigue crack growth mechanism investigation for aluminum alloys and steel," in *Proc. 54th AIAA/ASME/ASCE/AHS/ASC Struct., Structural Dyn., Mater. Conf.*, 2013, p. 1499.

[70] J. Bao, D. Guo, J. Li, and J. Zhang, "The modelling and operations for the digital twin in the context of manufacturing," *Enterprise Inf. Syst.*, vol. 13, no. 4, pp. 534–556, Apr. 2019.

[71] S. Mihai, M. Yaqoob, D. V. Hung, W. Davis, P. Towakel, M. Raza, M. Karamanoglu, B. Barn, D. Shetve, R. V. Prasad, H. Venkataraman, R. Trestian, and H. X. Nguyen, "Digital twins: A survey on enabling technologies, challenges, trends and future prospects," *IEEE Commun. Surveys Tuts.*, vol. 24, no. 4, pp. 2255–2291, 4th Quart., 2022.

[72] *Simulation vs Digital Twin (What is the Difference Between Them?)* [Online]. Available: https://www.twi-global.com/technical-knowledge/faqs/simulation-vs-digital-twin

[73] F. Tao, F. Sui, A. Liu, Q. Qi, M. Zhang, B. Song, Z. Guo, S. C.-Y. Lu, and A. Y. C. Nee, "Digital twin-driven product design framework," *Int. J. Prod. Res.*, vol. 57, no. 12, pp. 3935–3953, 2018.

[74] L. Wright and S. Davidson, "How to tell the difference between a model and a digital twin," *Adv. Model. Simul. Eng. Sci.*, vol. 7, no. 1, pp. 1–13, Dec. 2020.

[75] V. Raghunathan. (May 2019). *Digital Twins vs Simulation: Three Key Differences*. [Online]. Available: https://www.entrepreneur.com/en-au/technology/digital-twins-vs-simulation-three-key-differences/333645

[76] U. Sisodia. (Jun. 2011). *Creating an SoC Virtual Platform for Embedded Software Development*. [Online]. Available: https://www.electronicdesign.com/news/products/article/21759920/creating-an-soc-virtual-platform-for-embedded-software-development

[77] C.-C. Wang, R.-P. Wong, J.-W. Lin, and C.-H. Chen, "System-level development and verification framework for high-performance system accelerator," in *Proc. Int. Symp. VLSI Design, Autom. Test*, Apr. 2009, pp. 359–362.

[78] M. A. El-Moursy, A. Sheirah, M. Safar, and A. Salem, "Efficient embedded SoC hardware/software codesign using virtual platform," in *Proc. 9th Int. Design Test Symp. (IDT)*, Dec. 2014, pp. 36–38.

[79] G. N. Schroeder, C. Steinmetz, C. E. Pereira, and D. B. Espindola, "Digital twin data modeling with automationml and a communication methodology for data exchange," *IFAC-PapersOnLine*, vol. 49, no. 30, pp. 12–17, 2016.

[80] G. N. Schroeder, C. Steinmetz, R. N. Rodrigues, R. V. B. Henriques, A. Rettberg, and C. E. Pereira, "A methodology for digital twin modeling and deployment for industry 4.0," *Proc. IEEE*, vol. 109, no. 4, pp. 556–567, Nov. 2020.

[81] T. Riedelsheimer, S. Gogineni, and R. Stark, "Methodology to develop digital twins for energy efficient customizable IoT-products," *Procedia CIRP*, vol. 98, pp. 258–263, 2021.

[82] Baeldung. (Nov. 2022). *Inter-Process Communication*. [Online]. Available: https://www.baeldung.com/cs/inter-process-communication

[83] L. Vilanova, M. Jorda, N. Navarro, Y. Etsion, and M. Valero, "Direct inter-process communication (dIPC): Repurposing the CODOMs architecture to accelerate IPC," in *Proc. 12th Eur. Conf. Comput. Syst.*, Apr. 2017, pp. 16–31.

[84] L. Vilanova, M. Ben-Yehuda, N. Navarro, Y. Etsion, and M. Valero, "CODOMs: Protecting software with code-centric memory domains," *ACM SIGARCH Comput. Archit. News*, vol. 42, no. 3, pp. 469–480, 2014.

[85] M. Xue and C. Zhu, "The socket programming and software design for communication based on client/server," in *Proc. Pacific-Asia Conf. Circuits, Commun. Syst.*, May 2009, pp. 775–777.

[86] J. Postel, "Transmission control protocol," Tech. Rep., 1981.

[87] Z. Zhao, L. Shen, C. Yang, W. Wu, M. Zhang, and G. Q. Huang, "IoT and digital twin enabled smart tracking for safety management," *Comput. Operations Res.*, vol. 128, Apr. 2021, Art. no. 105183.

[88] Z. Jiang, Y. Guo, and Z. Wang, "Digital twin to improve the virtual-real integration of industrial IoT," *J. Ind. Inf. Integr.*, vol. 22, Jun. 2021, Art. no. 100196.

[89] Z. Wang, X. Liao, X. Zhao, K. Han, P. Tiwari, M. J. Barth, and G. Wu, "A digital twin paradigm: Vehicle-to-cloud based advanced driver assistance systems," in *Proc. IEEE 91st Veh. Technol. Conf. (VTC-Spring)*, May 2020, pp. 1–6.

[90] W. Xu, J. Cui, L. Li, B. Yao, S. Tian, and Z. Zhou, "Digital twin-based industrial cloud robotics: Framework, control approach and implementation," *J. Manuf. Syst.*, vol. 58, pp. 196–209, Jan. 2021.

[91] T. Kaarlela, S. Pieska, and T. Pitkaaho, "Digital twin and virtual reality for safety training," in *Proc. 11th IEEE Int. Conf. Cognit. Infocommunications (CogInfoCom)*, Sep. 2020, pp. 000115–000120.

[92] A. M. Karadeniz, I. Arif, A. Kanak, and S. Ergun, "Digital twin of eGastronomic things: A case study for ice cream machines," in *Proc. IEEE Int. Symp. Circuits Syst. (ISCAS)*, May 2019, pp. 1–4.

[93] G. Schroeder, C. Steinmetz, C. E. Pereira, I. Müller, N. Garcia, D. Espindola, and R. Rodrigues, "Visualising the digital twin using web services and augmented reality," in *Proc. IEEE 14th Int. Conf. Ind. Informat. (INDIN)*, Jul. 2016, pp. 522–527.

[94] M. Zhou, J. Yan, and D. Feng, "Digital twin framework and its application to power grid online analysis," *CSEE J. Power Energy Syst.*, vol. 5, no. 3, pp. 391–398, 2019.

[95] C. Qiu, S. Zhou, Z. Liu, Q. Gao, and J. Tan, "Digital assembly technology based on augmented reality and digital twins: A review," *Virtual Reality Intell. Hardw.*, vol. 1, no. 6, pp. 597–610, Dec. 2019.

[96] X. Ma, F. Tao, M. Zhang, T. Wang, and Y. Zuo, "Digital twin enhanced human-machine interaction in product lifecycle," *Proc. CIRP*, vol. 83, pp. 789–793, 2019.

[97] A. Joseph, M. Cvetkovic, and P. Palensky, "Predictive mitigation of short term voltage instability using a faster than real-time digital replica," in *Proc. IEEE PES Innov. Smart Grid Technol. Conf. Eur. (ISGT-Europe)*, Oct. 2018, pp. 1–6.

[98] N. Tzanis, N. Andriopoulos, A. Magklaras, E. Mylonas, M. Birbas, and A. Birbas, "A hybrid cyber physical digital twin approach for smart grid fault prediction," in *Proc. IEEE Conf. Ind. Cyberphysical Syst. (ICPS)*, Jun. 2020, pp. 393–397.

[99] W. Danilczyk, Y. Sun, and H. He, "ANGEL: An intelligent digital twin framework for microgrid security," in *Proc. North Amer. Power Symp. (NAPS)*, Oct. 2019, pp. 1–6.

[100] W. Danilczyk, Y. L. Sun, and H. He, "Smart grid anomaly detection using a deep learning digital twin," in *Proc. 52nd North Amer. Power Symp. (NAPS)*, Apr. 2021, pp. 1–6.

[101] A. Saad, S. Faddel, T. Youssef, and O. A. Mohammed, "On the implementation of IoT-based digital twin for networked microgrids resiliency against cyber attacks," *IEEE Trans. Smart Grid*, vol. 11, no. 6, pp. 5138–5150, Nov. 2020.

[102] M. Zhang, Y. Zuo, and F. Tao, "Equipment energy consumption management in digital twin shop-floor: A framework and potential applications," in *Proc. IEEE 15th Int. Conf. Netw., Sens. Control (ICNSC)*, Mar. 2018, pp. 1–5.

[103] X. Ma, J. Cheng, Q. Qi, and F. Tao, "Artificial intelligence enhanced interaction in digital twin shop-floor," *Procedia CIRP*, vol. 100, pp. 858–863, 2021.

[104] C. Gehrmann and M. Gunnarsson, "A digital twin based industrial automation and control system security architecture," *IEEE Trans. Ind. Informat.*, vol. 16, no. 1, pp. 669–680, Jan. 2020.
[105] X. F. Liu, M. R. Shahriar, S. M. N. Al Sunny, M. C. Leu, and L. Hu, "Cyber-physical manufacturing cloud: Architecture, virtualization, communication, and testbed," *J. Manuf. Syst.*, vol. 43, pp. 352–364, Apr. 2017.
[106] T. N. Nguyen, S. Zeadally, and A. B. Vuduthala, "Cyber-physical cloud manufacturing systems with digital twins," *IEEE Internet Comput.*, vol. 26, no. 3, pp. 15–21, May 2022.
[107] J. Guo, N. Zhao, L. Sun, and S. Zhang, "Modular based flexible digital twin for factory design," *J. Ambient Intell. Humanized Comput.*, vol. 10, no. 3, pp. 1189–1200, 2019.
[108] T. H.-J. Uhlemann, C. Lehmann, and R. Steinhilper, "The digital twin: Realizing the cyber-physical production system for industry 4.0," *Procedia CIRP*, vol. 61, pp. 335–340, Jan. 2017.
[109] T. H.-J. Uhlemann, C. Schock, C. Lehmann, S. Freiberger, and R. Steinhilper, "The digital twin: Demonstrating the potential of real time data acquisition in production systems," *Procedia Manuf.*, vol. 9, pp. 113–120, 2017.
[110] C. Li, S. Mahadevan, Y. Ling, S. Choze, and L. Wang, "Dynamic Bayesian network for aircraft wing health monitoring digital twin," *AIAA J.*, vol. 55, no. 3, pp. 930–941, Mar. 2017.
[111] A. J. Zakrajsek and S. Mall, "The development and use of a digital twin model for tire touchdown health monitoring," in *Proc. 58th AIAA/ASCE/AHS/ASC Struct., Structural Dyn., Mater. Conf.*, Jan. 2017, p. 0863.
[112] M. Strobl, M. Kucera, A. Foeldi, T. Waas, N. Balbierer, and C. Hilbert, "Towards automotive virtualization," in *Proc. Int. Conf. Appl. Electron.*, 2013, pp. 1–6.
[113] M. Safar, M. A. El-Moursy, M. Abdelsalam, A. Bakr, K. Khalil, and A. Salem, "Virtual verification and validation of automotive system," *J. Circuits, Syst. Comput.*, vol. 28, no. 4, Apr. 2019, Art. no. 1950071.
[114] C. Lee, S.-W. Kim, and C. Yoo, "VADI: GPU virtualization for an automotive platform," *IEEE Trans. Ind. Informat.*, vol. 12, no. 1, pp. 277–290, Feb. 2015.
[115] A. Rassolkin, T. Vaimann, A. Kallaste, and V. Kuts, "Digital twin for propulsion drive of autonomous electric vehicle," in *Proc. IEEE 60th Int. Scientific Conf. Power Electr. Eng. Riga Tech. Univ. (RTUCON)*, Oct. 2019, pp. 1–4.
[116] S. Venkatesan, K. Manickavasagam, N. Tengenkai, and N. Vijayalakshmi, "Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin," *IET Electric Power Appl.*, vol. 13, no. 9, pp. 1328–1335, Sep. 2019.
[117] M. R. Kabir, N. Mishra, and S. Ray, "VIVE: Virtualization of vehicular electronics for system-level exploration," in *Proc. IEEE Int. Intell. Transp. Syst. Conf. (ITSC)*, Sep. 2021, pp. 3307–3312.
[118] M. R. Kabir and S. Ray, "Exploring system-level coordination of vehicular electronics: A case study for traction control," Tech. Rep., 2022.
[119] Y. Liu, L. Zhang, Y. Yang, L. Zhou, L. Ren, F. Wang, R. Liu, Z. Pang, and M. J. Deen, "A novel cloud-based framework for the elderly healthcare services using digital twin," *IEEE Access*, vol. 7, pp. 49088–49101, 2019.
[120] H. Laaki, Y. Miche, and K. Tammi, "Prototyping a digital twin for real time remote control over mobile networks: Application of remote surgery," *IEEE Access*, vol. 7, pp. 20325–20336, 2019.
[121] J. I. Jimenez, H. Jahankhani, and S. Kendzierskyj, "Health care in the cyberspace: Medical cyber-physical system and digital twin challenges," in *Digital Twin Technologies and Smart Cities*. Cham, Switzerland: Springer, 2020, pp. 79–92.
[122] N. Dey, A. S. Ashour, F. Shi, S. J. Fong, and J. M. R. S. Tavares, "Medical cyber-physical systems: A survey," *J. Med. Syst.*, vol. 42, no. 4, pp. 1–13, Apr. 2018.
[123] O. Kocabas, T. Soyata, and M. K. Aktas, "Emerging security mechanisms for medical cyber physical systems," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, vol. 13, no. 3, pp. 401–416, May/Jun. 2016.
[124] Q. Wang, W. Jiao, P. Wang, and Y. Zhang, "Digital twin for human–robot interactive welding and welder behavior analysis," *IEEE/CAA J. Autom. Sinica*, vol. 8, no. 2, pp. 334–343, Feb. 2021.
[125] A. E. Saddik, "Digital twins: The convergence of multimedia technologies," *IEEE Multimed.*, vol. 25, no. 2, pp. 87–92, Apr./Jun. 2018.
[126] P. Skobelev, V. Laryukhin, E. Simonova, O. Goryanin, V. Yalovenko, and O. Yalovenko, "Developing a smart cyber-physical system based on digital twins of plants," in *Proc. 4th World Conf. Smart Trends Syst., Secur. Sustainability (WorldS4)*, Jul. 2020, pp. 522–527.
[127] R. G. Alves, G. Souza, R. F. Maia, A. L. H. Tran, C. Kamienski, J.-P. Soininen, P. T. Aquino, and F. Lima, "A digital twin for smart farming," in *Proc. IEEE Global Humanitarian Technol. Conf. (GHTC)*, Oct. 2019, pp. 1–4.
[128] A. M. Beacham, L. H. Vickers, and J. M. Monaghan, "Vertical farming: A summary of approaches to growing skywards," *J. Horticultural Sci. Biotechnol.*, vol. 94, no. 3, pp. 277–283, May 2019.
[129] J. Monteiro, J. Barata, M. Veloso, L. Veloso, and J. Nunes, "Towards sustainable digital twins for vertical farming," in *Proc. 13th Int. Conf. Digit. Inf. Manage. (ICDIM)*, Sep. 2018, pp. 234–239.
[130] P. Angin, M. H. Anisi, F. Göksel, C. Gürsoy, and A. Büyükgülcü, "AgriLoRa: A digital twin framework for smart agriculture," *J. Wireless Mob. Netw. Ubiquitous Comput. Dependable Appl.*, vol. 11, no. 4, pp. 77–96, 2020.

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