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A NOVEL DIGITAL TWIN MODEL TO SUPPORT INTELLIGENT ROBOTIC MANUFACTURING SYSTEM ACCORDING TO INDUSTRY 4.0 TRENDS.

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ABSTRACT

Data, Information, and knowledge models are vital research topics explored in recent years to support advanced manufacturing decisions through important systems. Today, several tools assist in modeling these parameters, one of which is known as Knowledge-Based Engineering Systems (KBES). A KBES integrates different knowledge types to support decisions and allows the incorporation of multiple types of manufacturing and organization standards to work in a variety of business contexts. With the increased complexity of industrial manufacturing systems caused by Industrial 4.0 trends such as digital manufacturing and cyber-physical technology like digital twins (DTs), the use of KBES is becoming an essential tool in Project Life Management (PLM) to ensure DT design is suitable to preserve the integrity of industrial standards. This paper aims to utilize Industry 4.0 trends, ISO standards, and the Computer Integrated Manufacturing Open System Architecture (CIMOSA) as a framework to build a KBES that assists in the development of a novel DT model. This model supports the design and implementation of a DT within the environment of an intelligent robotic manufacturing system. The proposed DT model is beneficial in preserving industrial standards in DT development and aids as a reference for the foundation of DTs design in other manufacturing environments. A case study is performed by applying the proposed DT model to the design and implementation of a DT within a basic pick-and-place system, proving its applicability and function in the support of intelligent robotic manufacturing systems.

Keywords: DIGITAL MANUFACTURING TWIN MODELS, DIGITAL MANUFACTURING TOOLS, INTELLIGENT MANUFACTURING, INDUSTRIAL INTERNET OF THINGS, MACHINE LEARNING

NOMENCLATURE

CIMOSA	Computer Integrated Manufacturing Open System Architecture
CPS	Cyber-Physical Systems
DTM	Digital Twin Model
DT	Digital Twin
DTs	Digital Twins
IIoT	Industrial Internet of Things
ISO	International Organization for Standardization
KBES	Knowledge-Based Engineering System
PERA	Purdue Enterprise Reference Architecture
PLM	Product Lifecycle Management
OME	Operational Manufacturing Environment
NGAS	Next Generation Automation Systems

1. INTRODUCTION

The advent of Industry 4.0 has heralded a new era in manufacturing, characterized by the seamless integration of advanced information and communication technologies into production systems. This paradigm shift towards digital manufacturing is poised to revolutionize the industry, offering unprecedented levels of efficiency, flexibility, and quality. Central to this transformation is the concept of the digital twin (DT), a virtual representation of a physical manufacturing system that enables real-time monitoring, simulation, and optimization of production processes. In this context, the modeling of data, information, and knowledge plays a crucial role in supporting intelligent decision-making in advanced manufacturing systems.

While there exist many exemplars showing how a DT is implemented within a specific field of intelligent robotic manufacturing, there is little in the way of resources that explain the DT design process and capture/relay the knowledge-based decisions made in the creation of the DTs. This paper aims to create a Digital Twin Model (DTM) using Knowledge-Based Engineering Systems (KBES) to fill the gap in this knowledge capture. To make the DTM applicable for Next Generation Automation Systems (NGAS) seen in Figure 1, the model was built regarding the industrial standards defined by the International Organization of Standards (ISO), the framework of Computer Integrated Manufacturing Open System Architecture (CIMOSA), and integrates the latest trends of Industry 4.0 including Industrial Internet of Things (IIoT) and machine learning. Through a case study involving a pick-and-place robotic operation, the proposed DTM was applied to the design process of a DT and its integration to the physical system, showcasing its potential to improve the planning, commissioning, and execution of manufacturing processes. This DTM introduces an effective tool to guide DT design with alignment to industrial standards without the need for extensive expertise or experience in the multidisciplinary subject.

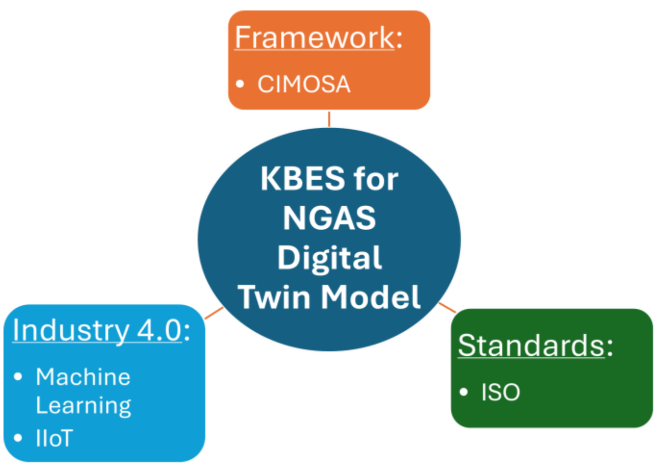

FIGURE 1: Framework of a knowledge-based engineering system (KBES) for digital twins in next-generation automation systems (NGAS).

2. LITERATURE REVIEW

2.1 Product Lifecycle Management (PLM)

Product Lifecycle Management (PLM) includes all the processes involved with the lifespan of a product: from conception, design, and manufacturing to sales and servicing, and finally disposal or repurposing. The utilization of PLM resources has been extensively observed across various companies in recent years, underlining the importance of digital tools in developing components, products, or assemblies throughout their lifecycle. Despite the extensive application, the lifecycle management process presents challenges, especially in the integration and effective utilization of digital tools.

The aerospace industry, exemplified by research initiatives at Kennesaw State University (KSU) in the Mechatronics Engineering Department, has demonstrated the effective use of Siemens PLM Software for virtual prototypes and simulations. This application is part of a broader strategy aimed at supporting the development of Next Generation Mechatronics Systems in the aerospace sector through the adoption of PLM technologies. By employing a novel framework that commences with selecting a PLM tool suitable for the specific lifecycle stage, KSU's strategy explores the potential applications of various PLM technologies for product and process development, alongside their integration [1].

In the context of Industry 4.0, the article emphasizes the transformative potential of digital technologies such as DTs, IIoT, and machine learning to address historical challenges faced by PLM implementations. These technologies promise to solve issues related to data collection, integration, and insight extraction, which have traditionally hindered the realization of PLM's full potential. The discussion highlights the emergence of Industry 4.0 as a critical enabler for the evolution of PLM systems, proposing future research directions and a roadmap for the realization of an integrated PLM by leveraging key Industry 4.0 technologies [2].

The work in [1] is particularly noteworthy for its practical application of PLM tools in an educational setting, preparing students for real-world challenges. Meanwhile, the work in [2] provides a comprehensive overview of the technological advancements that could redefine PLM systems, making them more efficient and integrated. It was observed that the convergence of PLM with Industry 4.0 technologies is a particularly exciting development. It not only addresses the historical limitations of PLM systems but also opens new avenues for innovation, collaboration, and sustainability in product development and lifecycle management. Both articles contribute valuable insights to the ongoing conversation about the future of PLM, emphasizing the need for continuous adaptation and integration of new technologies to meet the demands of the modern world.

2.2 Digital Manufacturing

Digital manufacturing represents a paradigm shift in how we conceptualize and execute the creation of goods, marking a departure from traditional methodologies that are heavily reliant on sequential processes to manage operations. To understand the structural differences between conventional and digitalized manufacturing, it's essential to consider the integration of product design, process design, and the automation of activities through object interaction with computerized components. This integration is a cornerstone of digital manufacturing, facilitating a seamless blend of physical and informational systems unlike anything seen in standard production and industrial manufacturing [3].

In the context of Industry 4.0, digital manufacturing systems are augmented with intelligent technologies such as IIoT, and big data analytics [4]. These technologies foster a highly adaptable and efficient manufacturing ecosystem capable of real-time monitoring, predictive maintenance, and autonomous decision-making. The DT concept plays a pivotal role here, acting as a bridge between the physical and virtual worlds, allowing for real-time data exchange and analysis, enabling manufacturers to anticipate issues, streamline operations, and innovate more rapidly.

The discussions in "Research on Intelligent Industrial Digital Manufacturing System Based on Industry 4.0 Computer Technology" [3] and "Virtual Commissioning for Advanced Manufacturing Using Digital Tools" [4] highlight the transformative impact of Industry 4.0 on manufacturing. These articles showcase the shift towards digitized, interconnected manufacturing environments that promise not only efficiency and cost savings but also a radical evolution in production methods.

2.3 Industrial Internet of Things (IIoT)

IIoT involves the use of plentiful and cheap sensors that can connect to the internet and provide real-time information about the inventory, status, and operation of devices and supplies in the manufacturing process. The IIoTs differ from the consumer IoT in that they focus on the infrastructure, manufacturing, and processes that can lead to business advantages [5].

The IIoT forms the base of the Next-Generation Automation System by providing the data and information that is used by the other systems. The IIoT increases the flexibility and interoperability of a system at the cost of the maintenance of vast amounts of data [6].

2.4 Digital Twins

DTs are defined as highly detailed digital models that represent physical manufacturing systems [7]. These virtual replicas are integrated with real-time data to mirror the physical state of their counterparts, enabling simulation, optimization, and control of manufacturing processes [8]. The concept significantly enhances the credibility of production systems, improving the efficiency of planning and execution processes. DTs serve as a bridge between the virtual and physical worlds, allowing for testing and validation of manufacturing scenarios and configurations before their real-world implementation. This integration leverages advancements in digital simulation and sensory data to foster rapid reconfigurability and self-updating capabilities within manufacturing systems, aligning with the flexible, sustainable, and efficient objectives of Industry 4.0.

The exploration of DTs in these articles underscores a transformative approach to manufacturing, showcasing how these virtual replicas can significantly enhance operational efficiency, reduce costs, and improve product quality. The dynamic interaction between DTs and their physical counterparts allows for real-time data exchange and optimization, marking a departure from traditional static simulations. This innovation aligns with Industry 4.0's emphasis on smart manufacturing, where data-driven decisions and digital advancements lead the way. Overall, DTs represent a pivotal step toward optimizing manufacturing processes and product lifecycle management through advanced digital modeling and real-time analytics.

2.5 Intelligent Automation

Intelligent Automation (IA) refers to the integration of artificial intelligence (AI) and automation technologies to create systems capable of performing tasks that traditionally require human intelligence. This includes learning from data, making decisions, and executing processes with minimal human intervention. IA combines the efficiency of automation with the cognitive capabilities of AI, such as machine learning, natural language processing, and computer vision, to enhance the automation of complex, decision-based tasks. The goal of Intelligent Automation is to improve productivity, accuracy, and efficiency in various operations while reducing the time and cost associated with manual processes. It is applied across multiple industries for tasks like data analysis, customer service, and process optimization, transforming the way businesses operate by enabling more scalable, responsive, and intelligent workflows [9].

2.6 Next Generation Automated Systems

Next-Generation Automation Systems (NGAS) is defined through the lens of integrating digital manufacturing tools, tacit knowledge capture, and the development of DTs. NGAS operates at the station level, connecting machines and humans, and implements knowledge modeling to provide design for manufacturability guidance within NGAS contexts [10]. The essence of NGAS, as discussed in this research, lies in capturing tacit knowledge—non-codified, experience-based knowledge—that is crucial for Industry 4.0. This tacit knowledge is integrated into the creation of DTs, which are virtual replicas of physical systems, enabling enhanced human-robot collaboration and smarter manufacturing processes. The research emphasizes the importance of tacit knowledge in advancing automation systems, ensuring they are more adaptive, intelligent, and capable of bridging the gap between physical and digital realms.

The focus on capturing and leveraging tacit knowledge within DTs is particularly compelling, highlighting a critical aspect often overlooked in discussions about automation and Industry 4.0. By valuing the unspoken, experiential knowledge of seasoned workers, NGAS promises to enrich automation systems with deeper insights and practical wisdom, potentially revolutionizing how we think about and implement automation in manufacturing. This research underscores the evolving nature of automation, where the integration of human knowledge and digital tools can lead to more intelligent, flexible, and efficient manufacturing systems.

2.7 ISO 23247-1:2021

ISO 23247-1:2021, "Automation systems and integration — Digital twin framework for manufacturing — Part 1: Overview and general principles," [11] offers a comprehensive framework that outlines how to establish and maintain digital representations that synchronize with their real-world manufacturing counterparts. This standard covers a wide array of applications, including real-time control, predictive maintenance, and engineering design, enhancing manufacturing operations' efficiency and adaptability. The standard is detailed in defining key terms and clarifying the roles of observable manufacturing elements such as personnel, equipment, and processes—essential for accurate digital representations. It highlights several benefits, such as improved production scheduling, enhanced risk management, and a better understanding of manufacturing processes, demonstrating how these architectures can lead to more efficient and adaptable manufacturing operations.

ISO 23247-1:2021 specifies essential requirements to ensure the functionality and effectiveness of these digital architectures within the manufacturing environment. These requirements focus on accuracy, communication, data acquisition, and integrity, crucial for the seamless integration and operation of digital architectures across various platforms. This standard plays a pivotal role as industries advance towards Industry 4.0, facilitating the integration of technologies like IIoT, machine learning, and big data analytics. Understanding and implementing ISO 23247-1:2021 is vital for developing sophisticated digital architectures that support the next generation of intelligent manufacturing systems. This paper's methodology leverages the structure and definitions provided by this standard to ensure the digital architectures are effective and compliant with current industry standards.

2.8 ISO/IEC 30173:2023

ISO/IEC 30173:2023, titled "Digital Twin – Concepts and Terminology," [12] provides a foundational framework for understanding and using DT technologies across various sectors. This standard is essential for ensuring that stakeholders across different domains have a consistent understanding and approach when implementing DTs.

The standard defines a "digital twin" as:

A digital representation of a physical entity connected by data enables the synchronization between the physical and digital states at an appropriate rate. This connection is vital for the DT's ability to perform functions such as simulation, optimization, and real-time decision-making based on the continuous flow of data from its physical counterpart.

ISO/IEC 30173:2023 outlines the framework and lifecycle processes of a DT, categorizing its applications into types such as component, asset, system, and process DTs. Each category serves different functions and purposes, demonstrating the versatility and depth of DT technology in enhancing operational efficiency and decision-making capabilities. By incorporating the principles and definitions from ISO/IEC 30173:2023, the research aligns with international standards, ensuring that the proposed DTM is both effective and interoperable within the global context of Industry 4.0 technologies.

3. METHODOLOGY

This section outlines the steps to create a DTM that aligns with Industry 4.0 trends. These steps ensure a comprehensive understanding and effective implementation of the DTM by detailing its components, standards, and frameworks.

1. Defining the Manufacturing System

   The initial step in developing a DTM involves defining the specific manufacturing system. An example is a system comprising several key components, including automated machinery and robotics, with a focus on a FANUC robot system. This robot is representative of the type of automated equipment used in advanced manufacturing settings and serves as a primary component in the proposed DTM. The DT represents both the physical and operational characteristics of this system, including its mechanical components, control systems, and interactions with other manufacturing processes.

2. Integration of System Components

   To effectively develop a DT, it is crucial to meticulously construct every component of the manufacturing system. This includes not only the primary machinery, such as the FANUC robot, but also auxiliary systems like conveyors, sensors, and operational software. Each component's specifications, behaviors, and interactions with other system elements must be accurately captured and integrated into the DT. This comprehensive approach ensures that the DT provides a true and accurate virtual representation of the physical manufacturing environment.

   Moreover, this process entails detailing the data flow and communication protocols between various components essential for real-time data synchronization and system responsiveness. Communication interfaces play a critical role in the standardization of Digital Twin frameworks as they enable interoperability, efficient data exchange, and seamless integration with IoT and other technologies. Standard interfaces facilitate scalability, reduce development costs, enhance security, and simplify upgrades and maintenance. They also promote innovation by allowing developers to focus on new applications rather than compatibility issues and support global collaboration by enabling entities worldwide to work together effectively. These benefits collectively drive the widespread adoption and effectiveness of digital twin technology across various industries. Through this integration, the DT can simulate and anticipate manufacturing outcomes with high fidelity, offering insights into the system's operational dynamics and identifying potential bottlenecks.

3. Framework and Model Definition

   Establishing a clear framework is crucial for the successful development of a DT. To accomplish this, the DTM adopted the Computer Integrated Manufacturing Open System Architecture (CIMOSA) as its framework. CIMOSA is specifically designed to facilitate the integration of computer systems within the manufacturing environment, making it an ideal choice for approaching DT modeling within an intelligent manufacturing system.

   Within the CIMOSA framework, the DTM serves as a detailed blueprint for constructing and scaling the virtual representation of the manufacturing system. It outlines the processes for data acquisition, processing, and utilization, enabling effective simulation and decision-making. The model also defines the interaction dynamics between various system components, ensuring that the DT behaves in alignment with the physical system under various operational conditions.

   This structured approach not only enhances the reliability of the DT but also provides a scalable method to adapt and expand the digital representation as new components are introduced or existing systems are upgraded.

4. Standards Identification

   Adherence to industry standards is a critical step in the development of DTM. Industry standards are essential because they provide a structured approach to DT development, aligning the DT with international best practices. This alignment ensures that the designed DT can interact seamlessly with other systems that follow the same standards, enhancing system compatibility and functionality.

   Among the pivotal standards that guide DT development are:

ISO 23247-1:2021(en): This part of the DT framework for manufacturing provides an overview and general principles, offering a foundational framework that guides the overall structure and integration strategies [11].

ISO 15531: Focused on industrial automation systems and integration, this standard is crucial for managing manufacturing data within the DT, ensuring robust data handling and storage [13].

ISO/IEC JTC 1/SC 41: The efforts of this committee focus on IIoT and DT standardization, supporting the integration of IIoT technologies with the DT for enhanced connectivity and data exchange [14].

ISO 22400: This standard provides guidelines for key performance indicators (KPIs) in manufacturing processes, crucial for measuring the efficiency and effectiveness of the DTM [15].

By adhering to these standards, we ensure that the DT is built on a solid foundation of proven methodologies and technologies, facilitating improved decision-making and operational excellence in manufacturing environments.

5. Industry 4.0 Trends and Technologies

A good DT needs to incorporate several key Industry 4.0 technologies to optimize its functionality and effectiveness in a modern manufacturing setting. These include:

IIoT (Industrial Internet of Things): Enables the interconnection of data among devices in a manufacturing system, such as sensors, computers and databases. By providing continuous input on operational status, IIoT enhances the accuracy and responsiveness of the DT, allowing it to mirror the physical environment with high fidelity.

Machine Learning and Artificial Intelligence: Empowers the DT with predictive analytics and intelligent decision-making capabilities. By analyzing data from IIoT devices and other sources, machine learning algorithms can predict system failures, optimize operations, and enhance overall manufacturing efficiency.

Cyber-Physical Systems (CPS): Integrates physical processes with computer-based algorithms and networking. CPS in DTs allows for real-time monitoring and control of the physical systems through cyber means, leading to more synchronized operations and flexibility in manufacturing.

Big Data Analytics: Enables the processing and analysis of vast amounts of data generated by the manufacturing system. This analysis helps in identifying patterns, trends, and insights, which can be used to improve the manufacturing process and the accuracy of the DT's simulations.

These technologies are the pillars of Industry 4.0, emphasizing interconnectivity, automation, and real-time data processing as foundational elements for modern manufacturing processes. By leveraging these advanced capabilities, the DT can achieve significant improvements in operational agility, predictive maintenance, system optimization, and resource management.

6. Digital Twin Model Definition and Development

To fully articulate the significance and functionality of the DTM, it is crucial to define it based on the standards previously mentioned.

The DT is not merely a static representation; it is a dynamic system that evolves in real time alongside its physical counterpart. This model leverages continuous data integration, simulates processes, predicts future states, and provides actionable insights to optimize manufacturing operations. Such a dynamic system exemplifies the principles of Industry 4.0 by enhancing connectivity, flexibility, and intelligence within the manufacturing environment.

Therefore, a DTM is a simplified representation of the structure and processes of a DT within the overall system. Various models can be created to demonstrate different views of the components or processes, as the CIMOSA framework suggests there are four views: function, information, resource, and organization. Since the model is focused on the design and implementation of a DT, the proposed model contributes a functional view, showing the required steps to design and implement a DT, an informational view, defining necessary components of the DT system to assist in planning, and a resource view, showing where standards are relevant and should be referenced when reaching that process in the DT's development.

4. DIGITAL TWIN MODEL

The DTM seen in Figure 2 visualizes the processes and requirements for DT design and implementation in a general manufacturing system. The model includes three subsections that each represent a distinct phase during the DT's development: the OME Definition phase, the Initial Digital Twin Design phase (Offline), and the Digital Twin Testing and Integration phase (Online).

OME Definition Phase:

The DT design process begins with identifying the Operational Manufacturing Environment (OMEs) in the targeted manufacturing system. An OME can be any object that has a physical presence or function that can be observed in a manufacturing process. According to ISO/IEC 30173 [12], this can include any personnel, equipment, material, process, facility, environment, product, or supporting documentation. Identifying and defining the targeted OME for the DT design helps to select technologies and methods that ensure the vital details of the OME are accurately represented and that the finished DTM is aligned with industrial standards to ensure manufacturing system integrity and easy universal integration with other standardized systems. Borrowed from the ISO/IEC 30173 suggested framework for DTs, there are five main considerations in the OME Definition phase:

1. **Select Identification Method:**
   - The identification method is how the DT system, components, and messages are identified when logging data and communicating with other systems. Using a single common identification method or one that is consistently used throughout the selected manufacturing system will simplify the implementation and interaction of the new DT with existing systems.

2. **Identify Data Types:**
   - Data types include important signals and data acquisition from sensors and processes of the OME. This also concerns the method of how data is communicated between systems, as adopting a common manufacturing message specification (MMS) or knowing how to convert the data from one MMS to another reduces the complexity and confusion of system integration.

3. **Identify Control Method:**
   - The control method is how both the OME and DT interact as part of the manufacturing system. This includes the feedback loop between the OME and the DT, deciding if the DT will also control the OME (driving DT) or just be a digital representation of the OME (driven DT), and implementing machine learning processes in the DT. For the system used in the following Case Study section, the OME DT is a driven digital representation.

4. **Select Digital Representation Software:**
   - Selecting a digital representation method considers how the DT will be virtually modeled, how the DT will be simulated in a virtual environment, and how the virtual environment will synchronize with the physical environment to allow for real-time processing. It is also decided which CAD, CIM, and CAM applications will be used to create and implement the digital representation. When deciding, it is important to choose applications that are standardized so CAD models can be easily imported into the DT software and that the DT software can easily export the DTM to other DT software for virtual testing and commissioning in various systems.

5. **Select Communication Protocols:**
   - Communication protocols are concerned with the physical communication method, the networking of ports, and the hierarchy of communication for IIoT applications. The main applications in DT design are physical-to-physical (OME-to-OME), physical-to-virtual (OME-to-DT), and virtual-to-virtual (DT-to-DT). ISO/IEC 30141 and ISO/IEC JTC 1/SC 41 specify the standards for IIoT design and ensure that OME and DT communication can be easily implemented in any existing system.

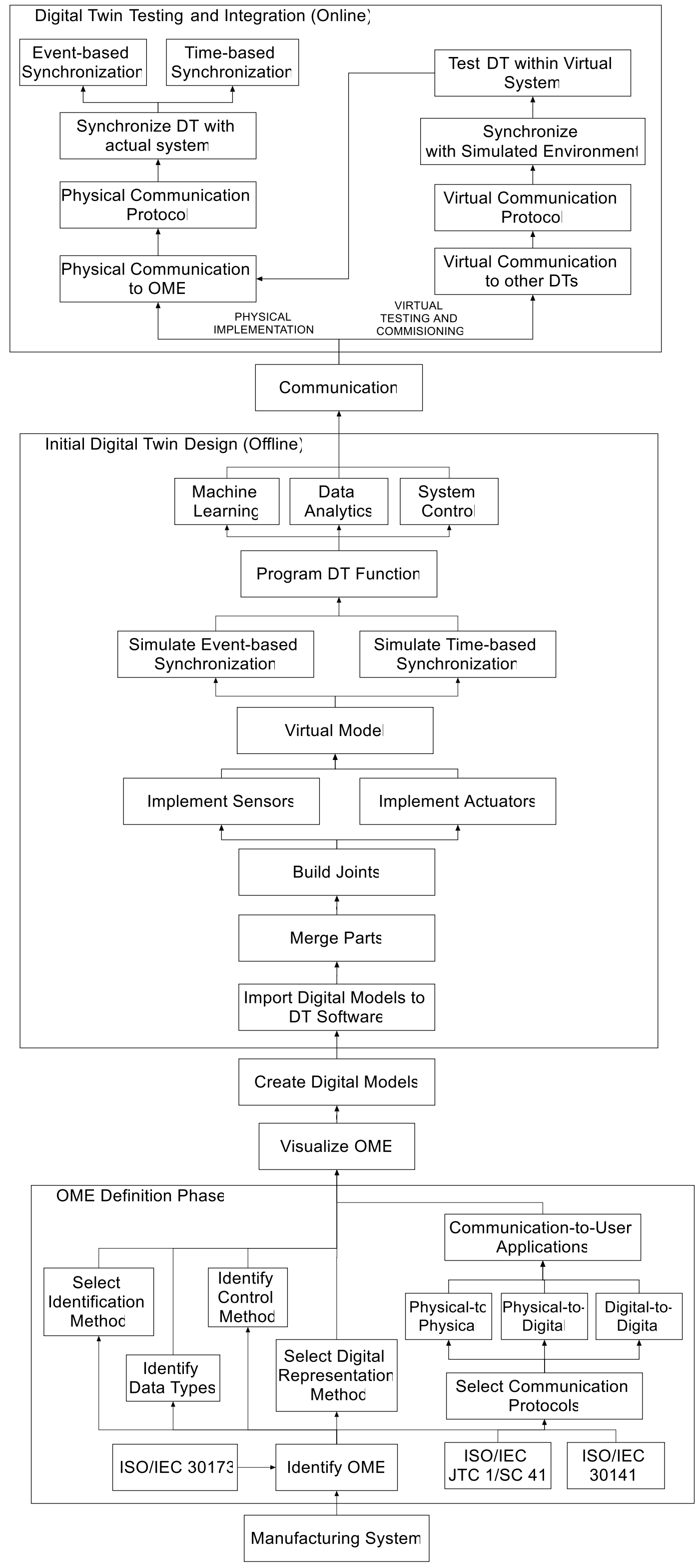

FIGURE 2: Digital Twin Design and Implementation Model for Intelligent Robotic Manufacturing Systems.

After identifying and defining the components of the OME, the OME is visualized in preparation for CAD digital modeling to represent the DTM based on either the physical OME's dimensions and specifications or the current design model if the physical OME does not yet exist.

Initial Digital Twin Design (Offline):

The initial design process is the creation of the DTM's visual representation and system functionality before it is integrated into the live system. This begins by importing the CAD digital model of the OME into the selected DT CIM software. Depending on the OME there may be several models that need to be imported and merged to within the DT CIM software to represent the whole OME. To replicate the kinetic operations of the OME, joints are defined within the DT CIM software to connect links and configured to movement properties of the physical system such as angle limitations and motion restrictions. Some OME's such as equipment, processes, facilities, or products may include actuators or sensors to represent the OME interaction with its environment and how it acquires data. Completing these steps results in a functional virtual model that includes details of motion and interactivity beyond the initial CAD digital model.

The next step is to create the DT process based on its functionality defined in the identify control method section of the OME definition phase. To build and test this functionality, the functional virtual model is simulated in the virtual environment of the DT CIM program. This environment utilizes computer-simulated time that the model and other objects in the simulation can synchronize with to create a common environment. This allows for the virtual execution of programmed interactions such as event-based triggers (a sensor being blocked) or time-based triggers (executing an action every five seconds). Once the model is simulated, it can be considered an offline DT.

The final step of the DT offline design is to implement the functionality of the OME and DT as mentioned in the OME definition phase. This includes data analytics, machine learning, and system control for both the DT and the OME.

Digital Twin Testing and Integration (Online):

Following the development of the offline DTM, the subsequent phase involves establishing communication between the DT and the Operational Manufacturing Environment (OME) or with other DTs, tailored to its specific functionality and purpose. Initially, the DT can either undergo virtual testing and commissioning within a simulated environment of interconnected DTs, or it can be directly linked to the physical OME.

In cases where the DT undergoes virtual testing, a virtual communication protocol already selected during the Digital-to-Digital communication phase of the OME definition is implemented to facilitate interaction between the DT and other DTs in the virtual environment. This setup ensures that all DTs synchronize seamlessly with the simulated environment, enabling realistic interaction scenarios crucial for effective commissioning and calibration of the DT.

Once the testing and commissioning phase is completed, or if this stage is skipped, the DT is integrated into the live OME. This integration begins by establishing a connection between the DT and the OME using the Physical-to-Digital communication method previously chosen during the OME definition phase. Upon successful connection, the virtual environment of the DT must be synchronized with the physical OME environment to accommodate both event-based and time-based actions. This synchronization ensures that the DT responds accurately to real-world conditions and triggers within the OME, facilitating a cohesive and efficient operational workflow.

6. CASE STUDY

Integration of Digital Twin Technology in FANUC Robotics Manufacturing System using Digital Twin Model

The case study explores the application of DT technology to the FANUC manufacturing system seen in Figure 3. By following the proposed DTM, this study demonstrates the process of using the tacit knowledge from the model to design and implement a DT into the existing FANUC system.

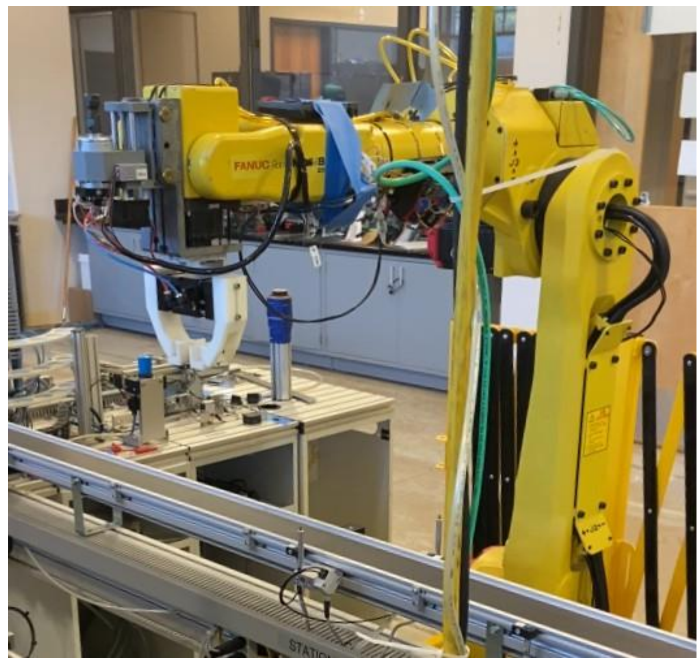

FIGURE 3: Multi-functional FANUC robotic arm with pneumatic parallel jaw gripper and drill tooling.

Defining the Manufacturing System

The kinematic characteristics of the FANUC robotics system were defined with detailed specifications. Figure 4 displays the robot's six degrees of freedom and the rotational limit of each joint, which is vital for replicating the system's movements in the digital model. The robotic system was designed with a custom end effector that combines a gripper and a drill tool. A sensor is attached to the drill to record the pressure applied to the tool when drilling into a part. The gripper function allows the robot to securely pick up, hold, and reposition workpieces while the integrated drill enables the robot to carry out drilling operations directly on the workpieces it handles. Capturing the functionality of the multifunctional tool is vital to understanding the operation of the FANUC system and how it interacts with the environment and other entities. The accurate modeling of this end effector and the system's kinematics properties is crucial for ensuring that the DT precisely mirrors the physical capabilities of the robotic system, thereby improving the simulation's effectiveness and applicability in real-world manufacturing scenarios. This system connects to its OME network using Node-RED, an adaptable, open-source platform used to wirelessly interface with Industry 4.0 technologies such as IoT devices and PLCs, which is ideal for integrating Industry 4.0 technologies with digital twins to optimize manufacturing processes.

Integration of System Components

A virtual environment was crafted using Tecnomatix PS software. This sophisticated platform simulates the kinematics of the system and the full operational dynamics of the FANUC robot and other entities in the virtual environment. Within the simulation, the robot's performance can be closely monitored, and system variables can be meticulously fine-tuned and tested before they are committed to the live system. For example, the drill speed of the end effector, which is a primary parameter for tool wear and number of drill cycles, can be simulated and validated for optimization of either or both of the resulting conditions before pushing the drill speed to the physical operation. By implementing this strategy, the development team can thoroughly assess potential improvements and identify any possible efficiencies within the robot's operations.

FIGURE 4: Fanuc's Kinematic Features

This preemptive analysis helps in pinpointing areas that require refinement, thereby ensuring that the DT not only mirrors the robot's function but also enhances its operation. Consequently, the DT emerges as an indispensable asset, significantly elevating the productivity and dependability of manufacturing processes by providing a seamless, risk-free medium to test and refine operations before they impact the production line.

Standards Identification and Adherence

The DTM adheres to several critical ISO standards, ensuring that it aligns with best practices:

1. **ISO/IEC 30173:2023:**
   - Standardized the communication protocol transmitted between the DT and the physical system using Node-Red, which established a uniform language and understanding essential for consistent application across industries.
2. **ISO 23247-1:2021:**
   - Established the monitoring procedure of the robot drill speed data. Outlines the DT framework for manufacturing, offering general principles for integration and operation, ensuring the DT effectively mirrors the physical manufacturing processes.
3. **ISO 15531:**
   - This standard was inherent to the design of the physical pick-and-place operation, which followed this specification's guidelines on manufacturing process specification and focuses on managing manufacturing data within industrial automation systems, critical for the DT's data handling capabilities. These characteristics were implicitly transferred to the DT.
4. **ISO 22400:**
   - Provides guidelines for key performance indicators in manufacturing processes, which are instrumental in assessing and optimizing the DT's performance. KPIs, such as drill speed and joint utilization, were captured as data points to assess the effectiveness of the DT.
5. **Efforts by ISO/IEC JTC 1/SC 42:**
   - While the contributions of this committee covers artificial intelligence, supporting the DT's ability to incorporate AI for smarter decision-making and operational intelligence, no artificial intelligence was demonstrated in this DT. Given AI's growing use cases in automation technologies, it is pertinent to highlight this standard's potential role nonetheless. A prospect of incorporating this standard for AI implementation for this case study would be to leverage deep reinforcement learning to conduct predictive modeling.

Incorporating Industry 4.0 Technologies

In line with Industry 4.0 advancements, the DT now incorporates state-of-the-art technologies such as IIoT and machine learning. By integrating these technologies, we've created a more interactive relationship between the digital and physical elements of the manufacturing system. IIoT devices provide ongoing insights into equipment performance, allowing for immediate adjustments and proactive responses to potential issues. Machine learning also plays a pivotal role by analyzing extensive operational data to identify patterns and predict future breakdowns, enabling preemptive maintenance strategies.

This strategic use of modern technology doesn't just optimize manufacturing processes; it revolutionizes them. It establishes a proactive maintenance system that significantly enhances efficiency and ensures equipment runs smoothly and reliably. These innovations are essential for pushing the boundaries of traditional manufacturing and moving towards a smarter, more resilient production environment.

7. RESULTS

The implementation of DT technology in the FANUC robotics system, guided by the proposed DTM, yielded substantial results offering valuable insights into potential enhancements in the manufacturing process and capturing the intricate dynamics of the FANUC system. This meticulous application of the methodology enabled a high-fidelity replication of the robotic system's behaviors and interactions within the virtual environment, ensuring that every aspect, from kinematics to operational responses, was accurately represented. The DTM facilitated an in-depth examination of the robot's complex movement patterns and its interactions with other manufacturing components, such as conveyors and fixtures, and ensured that the developed DT adhered to several industrial standards defined by ISO, facilitating a seamless integration to the existing system.

8. CONCLUSION

This study was successful in achieving the project goal of researching and producing a DTM for an intelligent manufacturing system built from a KBES integrating tacit knowledge from the CIMOSA framework, ISO standards, and Industry 4.0 components. The proposed model demonstrates the requirements and processes needed to develop a DT, contributing as a reference for DT design and implementation applications. This was supported in the case study as it exercised and demonstrated the utilization of the DTM in developing and implementing a DT into the existing pick-and-place system while keeping the DT within set industrial standards.

Concerning the project goal of offering a new perspective on DT modeling and integration of Industry 4.0, the DTM not only acts as a static diagram but serves as a foundation to continue building on as the industry continues to evolve with new technologies and standards. The intent of this article is not to validate a new framework but to explore and contribute to the possible applications of standardized frameworks for digital twins. By focusing on how existing standards can be applied across various industries, the article aims to highlight practical use cases and benefits. It seeks to demonstrate how standardized frameworks can enhance interoperability, data exchange, and overall efficiency in digital twin implementations, thereby driving innovation and collaboration. It provides a guide to each step of the DT design process from multiple points of the PLM. The process of designing the model also serves as a beneficial insight into knowledge-based engineering modeling, where the methods of capturing knowledge-based decisions and considerations for DTs could be referenced in developing models for other systems.

9. FUTURE WORK

While the CIMOSA framework was ultimately chosen as the most appropriate framework to reference for the structure of the DTM, there were some complications while using CIMOSA. One case was how the CIMOSA structure depended on four independent view dimensions to fully define an observed system. Given that the proposed DTM aimed to visualize the design and implementation processes of DTs, it required that several view dimensions such as functional and resource views be represented in a single model to properly achieve the DTM's goals, making the direct implementation of the framework convoluted. This complication suggests a need for investigation of current popular frameworks such as CIMOSA and PERA to determine if they can be improved upon to better suit system modeling of advanced manufacturing components like DTs, and if they are determined to be insufficient for this type of modeling, then there is perhaps a need for a new framework to be developed to adapt to the new advancements in technology.

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