Immersive Digital Twins: Combining IoT, VR, and Simulation for Smart Factory Environments

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Abstract. This work explores the development of a Digital Twin for an automated sorting system, combining real-time data integration via cloud services with immersive visualization in a virtual environment. The use case demonstrates how physical system behavior can be mirrored and monitored digitally, enabling interaction, remote insights, and enhanced user experience.

This work aims to highlight the integration challenges for different technologies. Key challenges included ensuring smooth communication, low latency, and consistent system representation across platforms.

Introduction

With the rise of Industry 4.0 and 5.0, a transformative shift is taking place in manufacturing, driven by data analytics, advanced automation, and the integration of intelligent systems [1].

This development has spurred growing interest in enabling technologies such as the Internet of Things (IoT), simulation, Virtual Reality (VR), and Digital Twins (DTs). Their relevance is particularly evident in the context of a shift from standardized mass production to customer-centric, highly customized manufacturing, which significantly increases the complexity of planning and operations [2].

Despite substantial progress in digitizing industrial systems, many companies still face challenges in effectively integrating real-time data, simulations, and immersive interfaces in a way that yields measurable benefits [3].

A notable gap exists in the literature regarding practical use cases that demonstrate the seamless interplay between simulation, IoT, and VR technologies in industrial environments.

The emergence of the industrial metaverse promises to bridge this gap by enabling highly interactive digital environments that mirror real-world manufacturing systems. Central to this vision is the use of DTs and real-time data to create responsive, lifelike digital counterparts. VR, in this context, serves as a key interface for immersive system interaction [4]. Achieving this requires the tight integration of diverse technologies, including IoT, digit Intelligence (AI), cloud platforms, and simulation tools. For example, [5] underlines the growing role of VR in manufacturing, while [6] demonstrates how combining VR and DTs can lead to more user-oriented systems.

While the foundational principles of DTs have been widely explored [7], [8], the interconnectivity of their components and integration with immersive technologies remains underrepresented in academic discourse. Recent studies [6], [9], [10] stress the importance of real-time, bidirectional connectivity between digital and physical layers, yet comprehensive integration approaches are still lacking.

This paper addresses that gap by presenting a case study focused on the implementation challenges of a DT with continuous, bidirectional data flow. Particular attention is given to the role of VR in enhancing real-time connectivity and enabling immersive interaction in a manufacturing context.

Beyond the technical aspects, the use case aims to explain the concept of a digital twin and its design considerations to a broader audience. This includes questions about the granularity of data integration, defining relevant system boundaries, and aligning virtual functionalities with real-world operational goals.

Accordingly, the demonstrator serves a dual purpose. On the one hand, it can be presented at public events to engage non-experts through interactive experiences and intuitive visualization. On the other hand, it provides a concrete, accessible basis for discussing economic potential, implementation strategies, and future research directions with decision-makers and research partners.

The subsequent sections describe the physical system and the integrated components in detail. The remainder of this paper is structured as follows: Section 1 provides theoretical background, including key definitions and technologies related to DTs. Section 2 details the methods applied in the case study, describing both the physical system and the setup of the digital and VR components. Section 3 presents and discusses the results of the implementation, highlighting the challenges and insights gained. Finally, Section 4 concludes the paper with a summary of key findings and an outlook on future research directions.

1 Theoretical Background

While significant research has been conducted on DTs and their applications in industrial settings, much of the existing work focuses on either theoretical models or isolated instances of DT implementation. Researchers such as [11], [12] have explored various aspects of DTs, particularly their potential for decision support and process optimization. This section focusses on explaining the current understanding of DTs and their key technologies.

1.1 Digital Twin

Since NASA first introduced DTs [7], the concept has evolved, with one definition describing DTs as dynamic virtual representations of physical systems that enable continuous, bidirectional data exchange. They support advanced functions such as real-time simulation, predictive optimization, and performance monitoring [13]. [8] break DTs down into three components: the physical system, its digital counterpart, and the data connections that integrate them.

DTs can be classified into three levels, with only the third being a complete DT. A Digital Model (DM) is static with no automatic data flow; a Digital Shadow (DS) adds one-way data flow from physical to digital; and a full DT features two-way communication, allowing real-time interaction [14].

While DTs and simulations both serve to model and analyze physical systems, their roles and integration levels differ. Simulations may incorporate real-time data and are valuable for forecasting and decision support, but they are typically operated as standalone tools without direct interaction with the physical system.

In contrast, DTs are persistently linked to their physical counterparts through continuous, bidirectional data exchange, enabling them to reflect the system's state in real time and actively influence it when needed [15][21].

1.2 DT Framework

The literature provides a multitude of frameworks for building DTs, but there is no universal method. [14] provide an overview of different types of frameworks that are commonly used. For the DT presented in this paper an approach according to [8] is chosen, where the three layers physical object, digital model and connection layer are described. Additionally, elements of the ISO 23247 framework are taken into consideration, particularly regarding layer modeling and the integration of a VR interface. ISO 23247 is a key standard for creating DTs in manufacturing. It offers a repeatable and adaptable procedure, developed by the ISO TC184/SC4 committee to support Industry 4.0.

The framework consists of 4 key domains, Observable Manufacturing Entities (OME's), which can be sensors, machines or products, data collection and device control, where data from the OME's is gathered, management, modeling and optimization, building the core of the DT and enabling analysis, simulation as well as system optimization and finally the user domain, an Interface for users and systems to interact with the DT services [16].

This combination of approaches was selected not only for its practical alignment with the DT described in this paper, but also for its compatibility with established standards in the field. By relying on widely recognized and adaptable frameworks such as those from [8] and ISO 23247, the approach addresses the pressing need for standardization in DT development. Utilizing such frameworks not only facilitates cross-industry applicability but also contributes to the ongoing efforts to define and validate common norms in the field of Digital Twins.

1.3 Applied Technologies

VR and AR enhanced by advances in AI, are increasingly integrated into DT systems.

These immersive technologies enable intuitive interaction with virtual objects and foster seamless collaboration with robotic systems, supporting safe and effective Human-Robot Interaction (HRI). Beyond technological innovation, there is growing awareness that the evolution toward Industry 5.0 must also prioritize human-centric values emphasizing well-being, sustainability, and resilience across industries, governments, and society as a whole [17].

Researchers in manufacturing and academia are increasingly exploring AR and VR to address complex industrial challenges. VR is widely used for applications such as virtual prototyping, machining, assembly, fault diagnosis, and training. AR enhances user interaction by overlaying digital information onto real-world processes, leveraging natural spatial abilities for improved situational awareness [18].

The IoT complements this transformation by establishing a densely interconnected network of intelligent devices capable of seamless communication and interaction.

By embedding computational intelligence into everyday objects and integrating them into a unified communication infrastructure, IoT enables both human-operated and autonomous systems to exchange data fluidly enhancing coordination, responsiveness, and system-wide efficiency [19]. The sensors used in this case study can all be seen as IoT devices.

In most real-world implementations, DTs incorporate AI or machine learning (ML) components to enable adaptive behavior, autonomous learning, and continuous performance optimization [20]. However, due to the scope of this work being limited to a demonstration showcase, such capabilities have not been integrated. For deployment in a production environment, the inclusion of AI/ML functionalities would be essential to fully realize the dynamic and self-improving nature of a DT.

These developments align with the concept of smart factories, which are digitally connected production environments that leverage technologies such as IoT, AI, and Cyber-Physical Systems (CPS) to enable real-time data exchange, autonomous decision-making, and continuous process optimization [21].

Within this context, DTs serve as a central component by providing virtual representations of physical assets and processes, supporting simulation, monitoring, and intelligent control across the production lifecycle [22].

2 Methods

This section describes the technical implementation of the system, covering its physical setup, the DT simulation, and the VR integration, all connected through a unified database to enable real-time, bidirectional communication.

2.1 Physical System

The system is designed to replicate a sorting process, in this case sorting by color. It consists primarily of two robotic arms: one is mounted adjacent to a conveyor belt, while the other is installed on a linear slide rail. In front of the first robotic arm is a grid that serves as an input area and is filled with colored cubes. This robotic arm is equipped with an integrated camera that captures an image of the input grid and transfers it to a graphical user interface (GUI). Within the GUI, the user can select the desired cube to pick up.

Next to the input grid, a staging area holds pallets to be placed on the conveyor before loading with cubes. The first robotic arm picks up a pallet, places it on the conveyor, and then places the selected cube on the pallet. As the conveyor transports the loaded pallet, a color sensor is positioned downstream to detect and validate the color of the cube. Upon successful color detection, the conveyor belt stops, allowing the second robotic arm mounted on the slide rail to retrieve the cube.

The second robotic arm then sorts the cube by placing it in one of four bins, each of which corresponds to a specific color: blue, red, yellow, or green. These bins are distributed at fixed intervals along the sliding rail. A camera mounted to the second robotic arm in addition to the information of the cube's color allows for those bins to be swapped out. The arm moves along the sliding rail until the camera has detected a bin with the same color as the current cube and then drops it. After sorting the cube, the robotic arm returns to pick up the now-empty pallet and place it on a return system, which consists of an additional conveyor belt.

Both robotic arms are controlled by Python scripts that manage task execution and inter-process communication using an SQL database. The Python-based GUI allows the user to choose between a local Docker-based SQL database and an online Azure SQL database, the latter allowing for remote communication and integration with external systems, such as an Omniverse connection.

After selecting a cube through the GUI, the automated sorting process is initiated.

2.2 Virtual Entity

For the development of the DT of the described system, a simulation was created using the AnyLogic simulation software. This virtual model replicates the exact physical layout of the real-world setup and maintains a live connection to the system via the Azure SQL database. This connection enables real-time, bi-directional information exchange, such as updates when a new cube enters the system or when a predictive maintenance (PM) event is triggered.

It's important to note that a virtual system isn't limited to a one-to-one representation of its physical counterpart. Rather, it can intentionally surpass the real-world system's boundaries by incorporating extra functionalities, abstractions, or enhanced complexity. In these instances, the physical system represents only a specific section or aspect of a broader, more comprehensive digital model.

Conversely, virtual representation may deliberately focus on a subset of a highly complex physical system. For example, it may model only selected components in the context of a digital twin or for targeted simulation purposes. Both approaches are valid, depending on the use case, and serve different objectives, such as facilitating predictive analytics, system optimization, or decision support.

In this specific example, there may be small differences between the physical system and the DT because of limited sensor availability. This can affect the accuracy of synchronization. To mitigate these effects and improve synchronization, all critical operations within the real system actively send status updates to the database, ensuring that the simulation reflects system activity as closely as possible.

To demonstrate the bidirectionality of the system, a predictive maintenance event is introduced into the simulation.

This event can be either random or manually triggered to simulate maintenance activities on the robot arms. During an ongoing PM event, the system suspends all user input to mirror real-world maintenance downtime.

The AnyLogic platform also provides both flowchart-based process visualization and detailed 2D and 3D visual representations of the facility, providing a comprehensive and dynamic view of system operations.

2.3 VR component and connectivity layer

The NVIDIA Omniverse platform is used to integrate the DT into a VR environment and enable user interaction with the system. Omniverse enables seamless integration of AnyLogic simulation models, allowing them to be imported directly into the VR environment, where they operate synchronously with the running simulation.

Like the Python script-based GUI, a virtual input grid is modeled within the Omniverse environment to enable user interaction. The cameras are used to detect cubes, and their colors are interfaced with the Python scripts that control the robotic arms. The results of these detections are continuously written to a central database.

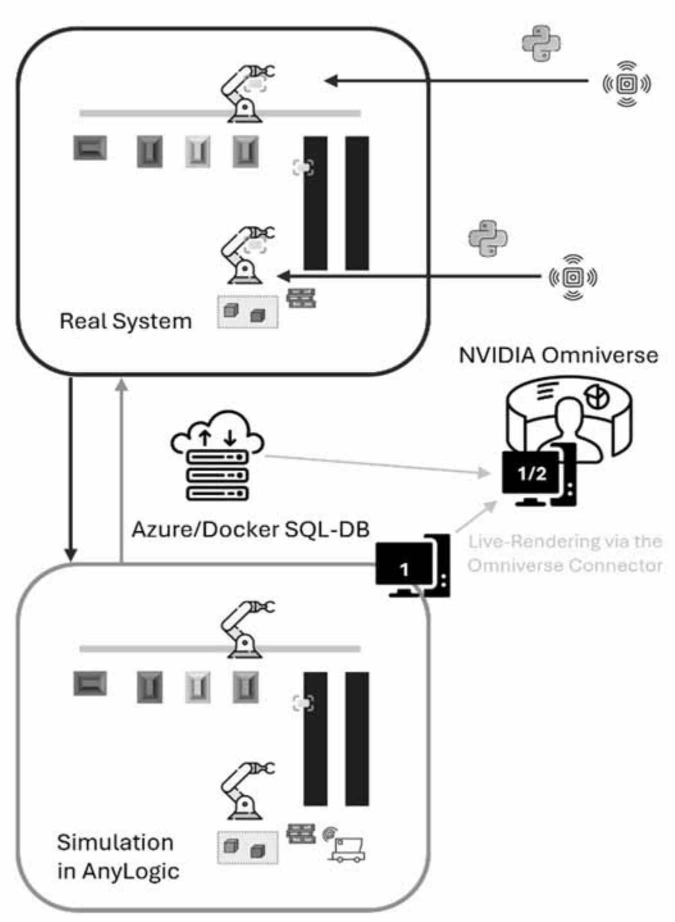

Figure 1: Overview of the overall structure of the use case.

The system supports two modes of operation: it can operate locally, using a PostgreSQL database hosted in a Docker container, but without a connection to the Omniverse. For universal access and real-time synchronization with the Omniverse platform, a switching mechanism is implemented within the scripts to allow the use of an Azure SQL database instead.

The database architecture consists of two tables: one table stores process-related information such as cube detection events and color classification, while the second table manages the data required to reconstruct the cube grid for input into the VR environment. This ensures that the visual representation of the cubes in VR accurately matches the camera detections made by the robotic arm.

A detailed overview of the overall structure can be found in Figure 1.

3 Results and Discussion

The proposed system was successfully implemented and the core components – physical setup, simulation model and virtual reality interface – were effectively integrated, see Figure 2. However, several challenges emerged during the development, which reflect broader, well-documented limitations in current DT implementations.

Figure 2: Physical setup and Omniverse implementation.

Initially, communication between the system components was planned via an MQTT broker. Although preliminary tests were promising, the reliability of the connection deteriorated in continuous operation. This observation is consistent with known problems in DT infrastructure regarding unstable or insufficient communication interfaces, as reported by [23]. To address this, the system architecture was modified to use an Azure SQL database, which significantly improved stability. Nevertheless, this solution introduced new constraints, such as the usage limitations inherent to the cloud-based service (in terms of free resources). These limitations were mitigated by dynamically generating database instances and adapting the Python scripts accordingly, requiring only minimal code changes.

Database integration within AnyLogic was achieved using a dedicated Java class, allowing consistent and real-time data synchronization between the simulation and the physical system. This approach supported the requirements of a DT, where real-world data continuously informs and updates the simulation model – an essential feature for improving system responsiveness and fidelity.

In contrast, the integration of the Omniverse-based VR component was more complex. While Omniverse provides a powerful platform for immersive system visualization, the lack of a stable real-time communication protocol between the simulation and the VR environment proved to be a critical bottleneck. As a temporary solution, data was exported and imported via JSON files to synchronize the VR state with database records. This workaround highlights the current lack of interoperability standards when bridging simulation environments and real-time 3D engines – another limitation identified by [23].

Furthermore, initial interaction concepts in the VR environment – in particular the use of conventional VR controllers for cube selection and task execution – were found to be error-prone.

In response, a custom interaction tool was developed in the form of a wand-shaped pointer. This tool significantly improved input precision and user control, improving the overall user experience and reducing the likelihood of unintended actions. This highlights the importance of user-centered design in computerized environments, particularly where immersive and real-time interaction is required.

Although the system did not rely heavily on physical sensor integration, there were still significant technical challenges in ensuring consistent data flow and maintaining system responsiveness. One of these problems being the camera sensors not consistently detecting the same or right colors for the cubes. Reasons being different lighting or over/under-fitting of color spectrums, causing a flicker in the GUI.

These experiences are consistent with concerns raised in the literature about the computational demands and high overhead associated with DT development, even for relatively small-scale implementations [23]. Overall, the project illustrates both the practical feasibility and the complexity of building networked, interactive DT systems that span physical automation, simulation environments and immersive interfaces.

4 Conclusion and Outlook

The acquisition of cross-domain knowledge proved essential during the development of this case study. However, such interdisciplinary learning is rarely a viable strategy in commercial settings, where time constraints and project complexity typically necessitate the collaboration of dedicated domain experts. This reliance on specialized knowledge underscores a key limitation when attempting to scale custom-built systems beyond the academic context.

While the system was internally consistent and tailored to the specific requirements of this study, the lack of standardization presents a major challenge when scaling up or involving external stakeholders. As more individuals or companies become part of the development or deployment process, interoperability issues and system complexity tend to increase significantly. Furthermore, the system's reliance on stable and fast internet connectivity poses a major vulnerability; any connectivity issues could severely impair performance or even halt operations altogether. Lastly, security considerations were not a primary focus in this study, given its academic nature. However, in real-world industrial applications, especially those involving sensitive or proprietary data, robust security measures are absolutely critical and cannot be overlooked.

Further improvements can enhance the system's reliability and autonomy. For instance, the first robotic arm could be equipped with an improved lighting source to increase the accuracy of color detection.

Additional sensors may be integrated to enable better real-time synchronization with the simulation. Moreover, various operational modes could be implemented for demonstration purposes, including a fully automated mode requiring no user interaction. As the use case continues to evolve, the underlying code will also undergo ongoing optimization – particularly regarding performance, where further enhancements remain possible.

Publication Remark

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