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SIMULATION ASPECTS OF A GENERIC DIGITAL TWIN ECOSYSTEM FOR COMPUTER NUMERICAL CONTROL MANUFACTURING PROCESSES

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ABSTRACT

This work considers a generic Digital Twin Ecosystem (DTE) for computer numerical control manufacturing processes. The DTE aims to accurately model physical systems' behavior in 3D virtual space, improve stakeholder decision-making based on real-time analytics, and generate insight for autonomous process intervention. The DTE uses the Unity real-time development platform to integrate online simulation for process replication, remote monitoring and management of the manufacturing process, and offline simulation for "what-if" analysis and exploration of process variables under various operational scenarios. Online and offline simulation could be combined to enhance twinning with predictive capabilities for timely autonomous intervention. In this work, we describe the architecture of the generic DTE, detail its components, and demonstrate its universal applicability through two case studies in Additive and Subtractive Manufacturing. We also discuss simulation aspects of the DTE, focusing on process replication and process lookahead.

1 INTRODUCTION

Industry 4.0 (I4.0) (Lasi et al. 2014), also known as the fourth industrial revolution, originated in Germany, where it was introduced as a strategic initiative by the government (Rojko 2017). The concept emphasizes the need for flexible, individualized, and customized production and has the potential to improve production processes, increase productivity, and create new business models (Pereira and Romero 2017). I4.0 represents a paradigm shift towards more connected, intelligent, and efficient industrial processes, driving innovation and transformation across various sectors.

At its core, I4.0 integrates the physical and the digital worlds (Pereira and Romero 2017; Vaidya et al. 2018) to generate reliable and easily traceable data flows or better utilize existing data to facilitate improved data-driven decision-making. A Digital Twin (DT) is a virtual replica of a real-world object, process, or system developed by integrating real-time data, computational models, and simulation techniques. DTs are an essential component of I4.0 and can be utilized to reveal data flows that were previously hidden or overlooked and to generate new data. DTs are utilized in many fields, such as energy (Do Amaral et al. 2023), construction (Yitmen et al. 2021), and manufacturing (Hyre et al. 2022; Osho et al. 2022).

The concept of Digital Twins (DTs) is a key enabler in the digital transformation of manufacturing, with various definitions and applications across the field (Negri et al. 2017; Kritzinger et al. 2018; Fuller et al. 2020). The original concept was presented by Grieves (Grieves 2005) in the context of product life-cycle management and considers a DT as a virtual representation of a physical product. In later work, Grieves revisits the DT and describes it as a three-component construct consisting of: i) a physical product, ii) a virtual representation, and iii) a bi-directional data exchange between the physical and the virtual domain (Grieves 2014). In the work of Negri et al. (2017), a manufacturing DT is defined as "*A virtual representation of a production system that is able to run on different simulation disciplines that is characterized by the synchronization between the virtual and real system, thanks to sensed data and connected smart devices, mathematical models and real-time data elaboration. The topical role within Industry 4.0 manufacturing systems is to exploit these features to predict and optimize the behavior of the* *production system at each life cycle phase in real time.*" This definition is the closest to how a DT is considered in this research.

Our work considers a generic Digital Twin Ecosystem (DTE) for Computer Numerical Control (CNC) manufacturing processes. The DTE offers two operational modes: i) the online simulation mode and ii) the offline simulation mode. Online simulation can be utilized for real-time process replication, remote monitoring, and management of the manufacturing process, while offline simulation for "what-if" analysis and exploration of process variables under various operational scenarios. These modes can be used standalone or in combination. When the operational modes are combined, the DTE gains process lookahead capabilities, meaning it could predict the effect of future actions on the manufacturing process. Future insight could be fine-tuned based on real-time data flows available to the DTE. The focus of this manuscript is to discuss the architecture of the generic DTE and demonstrate its universal applicability. To this end, we present an Additive Manufacturing (AM) and a Subtractive Manufacturing case study. The focus of this work is also to discuss simulation aspects of the DTE methodology considering process replication and lookahead.

The rest of this manuscript is organized as follows: In section 2, we discuss related research focusing on the role of simulation in DTs. In section 3 we introduce the DTE, describe its components, and present two case studies. In section 4, we discuss simulation aspects of the DTE, focusing on process replication and lookahead. Finally, in section 5, we provide conclusions and future research directions.

2 RELATED WORK

In recent years, researchers have attempted to shed light on the differentiation between a DT and a simulation model (Wooley et al. 2023; Taylor et al. 2021; Shao et al. 2019). However, there is still a lack of consensus, with people claiming that simulation models are DTs. A traditional simulation model differs from a DT because it lacks crucial twinning elements, such as real-time process replication, synchronization with the physical system (Biller et al. 2022), and bidirectional data exchange. The work of Kritzinger et al. (2018) proposes a classification of DT literature based on the level of data integration. The representation of a physical system in the virtual domain without data exchange is classified as a Digital Model. If a Digital Model incorporates a unidirectional data flow from the physical to the digital realm, it is classified as a Digital Shadow. Finally, if a Digital Model features a bidirectional data exchange and can intervene in the operation of its physical counterpart to some degree, it is classified as a DT. The generic DTE proposed in our work meets the requirements of the DT category since it implements bidirectional data flow. Process data are acquired by the physical system and are used for real-time process replication, monitoring, analytics, and "what-if" analysis. Furthermore, the DTE has direct access to the machine control software and can issue commands to modify the operation of the physical asset.

It is safe to state that any DT could encompass one or more simulation models. The work of van der Valk et al. (2020) investigates the different kinds of simulation models in DTs and proposes a taxonomy. These models can be static or dynamic, discrete or continuous, deterministic or stochastic (Law et al. 2007). The granularity of such models can differ to provide multiple views of the physical system. Finally, their time horizon could be finite or infinite. In the work of Makarov et al. (2019), simulation methods are used to create DTs for production enterprises. Furthermore, Kuhn et al. (2020) presents a rule-based simulator coupling architecture for DTs. In the work of Reed et al. (2021), the authors introduce a Discrete Event Simulation modeling cycle for DTs and highlight the need for specialized software tools. These studies demonstrate the close relationship between simulation and DTs, which often becomes the reason the two concepts are falsely used interchangeably. Traditional simulation models have tremendous value and are suitable decision-support tools for a plethora of applications, but they should not be presented as DTs.

DTs are gaining popularity in manufacturing as technology continues to advance. Improvements in the interoperability and connectivity of industrial equipment facilitate the development of sophisticated DT applications. Examples include virtual commissioning (Mykoniatis and Harris 2021), performance optimization, predictive maintenance (van Dinter et al. 2022), production planning and control (Agostino et al. 2020), human-robot interaction (Gallala et al. 2022), safety training (Kaarlela et al. 2020), secure cyber-physical system design, intrusion detection, anomaly detection, and penetration testing (Eckhart and Ekelhart 2019). A substantial body of research has explored the application of DTs in machining, offering various perspectives and methodologies. The work of Cabral et al. (2023) proposes a DT architecture for a CNC Hass Mini Mill machine using the ISO 23247 standard. The work of Ganser et al. (2021) examines the enabling role of Industrial Internet of Things for machining DTs. The work of Plakhotnik et al. (2021) attempts to combine digital representations of different objects involved in the machining process in a holistic manner. Hänel et al. (2021) integrates models for process parameters in a DT information system with the purpose of model-based analytics.

A range of studies have explored the use of game engines in simulation and DTs. One of the most popular game engines is Unity. Unity provides essential features that can be utilized for modeling & simulation. It includes a real-time rendering pipeline, enabling dynamic and immersive environments. Furthermore, Unity's robust physics engine allows for realistic object interactions in 3D space. Another important aspect of Unity is its scripting capability, which enables the implementation of complex behavior. The work of Wang et al. (2021) specifically focuses on the use of Unity for simulating connected and automated vehicles. Similarly, Dosoftei (2023) highlights the potential of Unity's immersive capabilities in creating DTs for mechatronic systems. The work of Dong et al. (2020) focuses on model optimization and uses Unity to visualize an intelligent production line running process. In Krstić and Mekterović (2018), the authors use Unity's powerful physics engine to study the properties of ideal gases. Considering DTs in manufacturing, Pajpach et al. (2022) uses Unity and the Open Platform Communications Unified Architecture (OPC UA) standard to create an educational development DT of a conveyor line. In Geng et al. (2022), the authors use Unity to realize a modular DT with Augmented and Virtual Reality capabilities. They validate the applicability of the proposed system through a case study on a CNC milling machine. The work of Borra et al. (2023) employs Unity to create a DT for CNC machines with the goal of detecting sensor and actuator failures remotely. In Zhu et al. (2023), Unity is utilized to construct a DT for a milling robot, effectively simulating the milling path and the material removal. These works underline the diverse applications of Unity in simulation and DT development. Due to these reasons, we use Unity in the DTE.

3 A GENERIC DIGITAL TWIN ECOSYSTEM (DTE)

The DTE methodology is machine-agnostic and is composed of two key components, namely i) the Data Acquisition Processing Distribution Component (APDC) and ii) the Virtual Representation Component (VRC). The orchestrated interweaving of these components comprises a software ecosystem that enables bidirectional data exchange between the physical manufacturing asset and its digital counterpart. A high-level architecture diagram of the DTE is illustrated in Figure 1. More details about the APDC and the VRC are provided in sections 3.1 and 3.2, respectively.

3.1 Data Acquisition Processing Distribution Component (APDC)

This component has an open communication bus with the machine control software for bidirectional data exchange. It is responsible for acquiring machine data, processing them, and making them available to other components or services. The data acquisition function involves establishing a connection with the machine control software so that machine data can be retrieved. The data processing function involves transforming unstructured machine data into a structured format for consumption by external services. It could also include synthesizing new data based on the acquired machine data. The data distribution function considers making data available to external services via a wired or wireless connection using various communication protocols. Each protocol offers unique strengths, addressing different requirements and use cases in DT applications. Some of these protocols are described below:

- Representational State Transfer (REST), based on Hypertext Transfer Protocol (HTTP), provides a standard for accessing and manipulating resources using a stateless communication model commonly

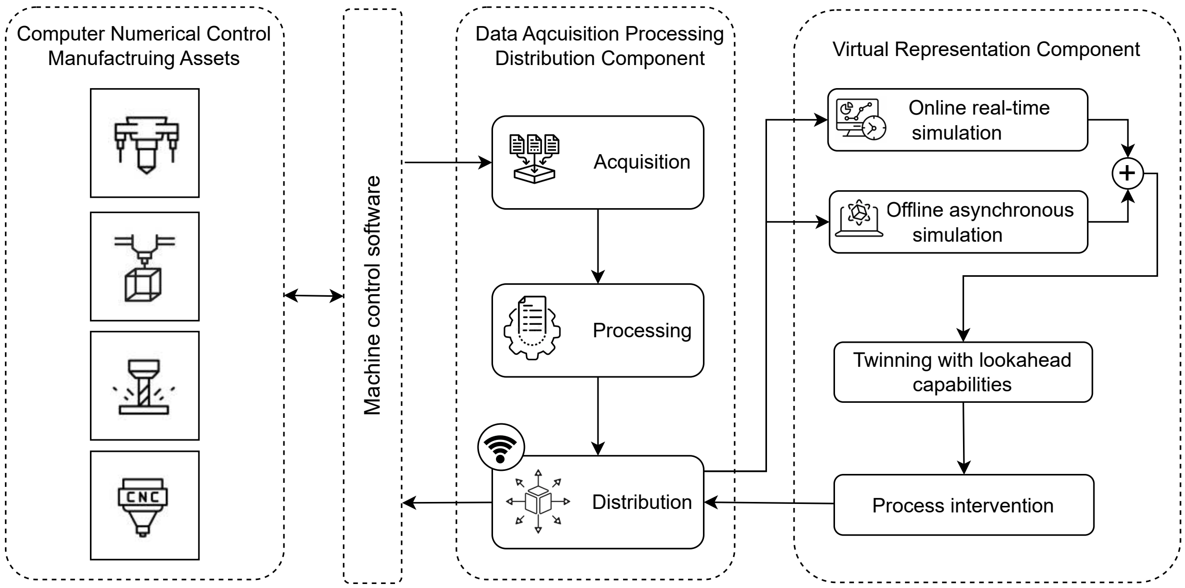

Figure 1: High-level Digital Twin Ecosystem architecture diagram.

used for periodic updates and status queries in DTs. We use REST in our first DTE case study on Additive Manufacturing (section 3.3.1).

- WebSockets enable full-duplex communication between clients and servers over a single Transmission Control Protocol (TCP) connection, making them suitable for maintaining synchronized states and enabling low-latency bidirectional data exchange. We use WebSockets in our second case study, considering Subtractive Manufacturing (section 3.3.2).
- MQTT is a lightweight publish-subscribe messaging protocol frequently used in Internet of Things (IoT) applications, allowing efficient real-time data exchange over TCP/IP. IoT refers to a network of interconnected devices that are embedded with sensors, software, and other technologies to collect and exchange data over the Internet. Data flows generated from such devices can be incorporated into the APDC in a straightforward manner so that machine data are enriched with external sensor data for a more complete representation of the physical process.
- OPC UA is a robust industrial communication standard facilitating secure and reliable data exchange between machines and systems, supporting complex data modeling and interoperability.
- MTConnect is a protocol tailored for manufacturing environments and uses HTTP and Extensible Markup Language (XML) or JavaScript Object Notation (JSON). MTConnect is utilized for interoperability and real-time monitoring of shop floor equipment, making it suitable for DTs in industrial settings.

Data distribution also encapsulates the ability of the APDC to issue commands to the machine control software. In the context of the DTE, this component serves as an interface between the physical manufacturing asset and the VRC.

3.2 Virtual Representation Component (VRC)

This component is responsible for modeling the physical manufacturing process in the virtual domain. Its tasks include accurately recreating physical components and their relationships based on data made available via the APDC. Virtual representation encompasses structural and behavioral aspects, such as 3D geometry, movement constraints, and machine component properties and dependencies. We utilize the Unity real-time development platform to build the VRC. Unity offers a set of features that are useful in creating robust and realistic virtual representations of physical processes or systems. Such features include a rendering pipeline, a physics engine, and versatile interconnectivity and scripting capabilities. To recreate the physical entity in virtual space, we approach each distinctive physical part as an object. Objects have inherent properties and relationships with other objects. For example, consider the spindle of a machine which would be modeled in Unity as follows:

- Search for a 3D model of the physical spindle or create it using Computer-Aided Design (CAD).
- Import the 3D model in Unity.
- (Optional) Scale the object's mesh to accurately reflect its X, Y, and Z axis dimensions.
- Define and populate the properties of the object. For example, minimum and maximum attainable revolutions per minute.
- Group the object with other objects that share the same behavior. For instance, a spindle should be grouped with the collet that grips the tool and secures it in place. Grouped objects will move and rotate together.
- Place the object or group of objects at the appropriate hierarchy level based on relationships with other objects. For example, if the spindle is mounted on the z-axis of a machine, the spindle-collet group will be a child of the z-axis.
- Attach a collider to the object. Colliders enable collision detection and physics simulation in virtual space powered by Unity's physics engine. The collider can be identical to or approximate the geometry of the object. This step can utilize primitive (box, sphere, capsule), compound, or mesh colliders. Choosing the appropriate collider type depends on factors such as accuracy, performance, and complexity of the DTE application.

The steps detailed above are applied to all components of interest in the physical manufacturing asset. The number of components modeled this way dictates the granularity of the DTE.

As illustrated in Figure 1, the two main functions the VRC implements are i) online real-time simulation, which refers to process replication, and ii) offline asynchronous simulation, which describes the capability for "what-if" analysis utilizing a G-code file and the machine's configuration settings. When these functions are combined, the VRC provides twinning with lookahead capabilities, which refers to its capacity to simulate what will happen in the future of program execution. More details about the VRC's simulation workflows are provided in section 4. The insight generated by process lookahead can be utilized for improved decision-making and autonomous process intervention. Subsequently, the VRC issues one or more commands to adjust the operation of the physical asset. This adjustment becomes possible via the distribution function of the APDC, which forwards the correction to the machine control software after making the necessary formatting, effectively completing the closed feedback loop of the DTE.

3.3 DTE Application Case Studies

The idea behind the DTE is to design and develop a generic unified platform for twinning and simulation applicable to machines that use G-code commands. To evaluate the universality of our method, we have applied the DTE methodology to two case studies. The first case study considers an Additive Manufacturing Fused Filament Fabrication machine (3D printer). The second case study considers a Subtractive Manufacturing 5-axis CNC mill. These case studies assisted us in gaining a more comprehensive understanding of the DTE's applicability, effectiveness, and areas for improvement. Through hands-on experience, challenges emerged that were not originally thought of. Some of these challenges consider the data acquisition infrastructure, networking protocols, data processing workflows, the determination of a suitable polling rate, accessing complete process data, and matching process data to their respective virtual domain components. By examining different manufacturing case studies, we were able to identify common patterns and differences and also assess the robustness and adaptability of the DTE methodology. More details about these case studies are provided in the following paragraphs.

3.3.1 Case Study 1: 3D Printer (Additive Manufacturing)

In the first study, we used a Lulzbot TAZ Workhorse 3D printer as our testbed. The APDC was developed using a Raspberry Pi Model 3 microcomputer, which hosted Octoprint, an open-source 3D printer control software. External sensors were installed to enrich the data flows generated by Octoprint. Machine data and sensor data were post-processed, formatted, and made available via a REST API written in Python using the Flask web framework. The VRC was developed using Unity, and custom logic was written using the C# programming language. The end result was a DTE that could acquire and distribute machine and sensor data in near-real time. Furthermore, it could replicate the printer's behavior in 3-dimensional space, monitor variables of interest, and generate reports. Figure 2 illustrates the physical machine and its twin in the virtual domain. Readers are encouraged to find a detailed narration of our implementation and results in Pantelidakis et al. (2022). There, we describe software and hardware components, external sensors, physical to digital space mapping, VRC state transitions, as well as the experimental evaluation considering position, temperature, job duration, and response time. An online demo (demo 1. 2022) is also provided.

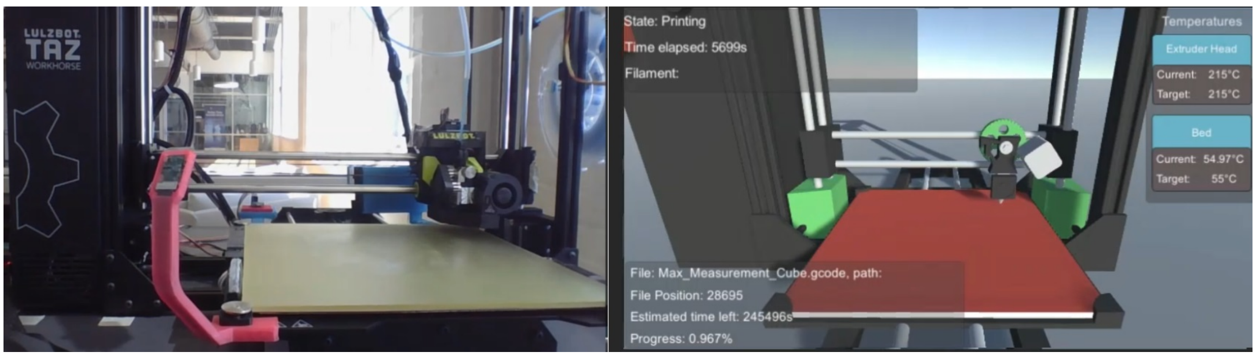

Figure 2: Left: Lulzbot TAZ Workhorse. Right: Process replication in the virtual domain captured from the Virtual Representation Component (Unity real-time development platform).

3.3.2 Case Study 2: 5-Axis CNC Mill (Subtractive Manufacturing)

In the second case study, our testbed is a Pocket NC V2-10 CNC desktop mill. This time, the DTE combines online real-time process replication with offline asynchronous G-code simulation. Offline simulation becomes possible via a custom G-code interpreter we wrote using the C# programming language. The interpreter receives G-code commands as input and calculates their effect on the machine, including the duration of command execution. The architecture of the DTE remains consistent, using the APDC for data acquisition, processing, and distribution. The APDC has direct access to the machine control software, LinuxCNC. The VRC is developed in Unity, which communicates with the APDC using the WebSockets communication protocol. Figure 3 illustrates the Pocket NC V2-10 and its twin in the virtual domain. Readers are encouraged to find more details in Pantelidakis and Mykoniatis (2024), including software infrastructure and hardware components, the G-code preprocessing workflow, the implementation of our custom C# interpreter, our duration estimation algorithm in pseudocode format, and our experimental evaluation regarding sequencing, seamless integration, and response time. An online demo (demo 2. 2024) is also provided.

4 SIMULATION ASPECTS OF THE DTE

In this section, we detail the role of simulation in the DTE. Simulation is an essential component of any DT and is utilized in different forms to enable DTE functionalities, as illustrated in Figure 4.

At the center of our methodology is access to machine control software. Bidirectional communication between the DTE and the machine control software lays the foundation for a successful DTE implementation. Manufacturers today face challenges considering access to machine data. Another issue is limited vendor

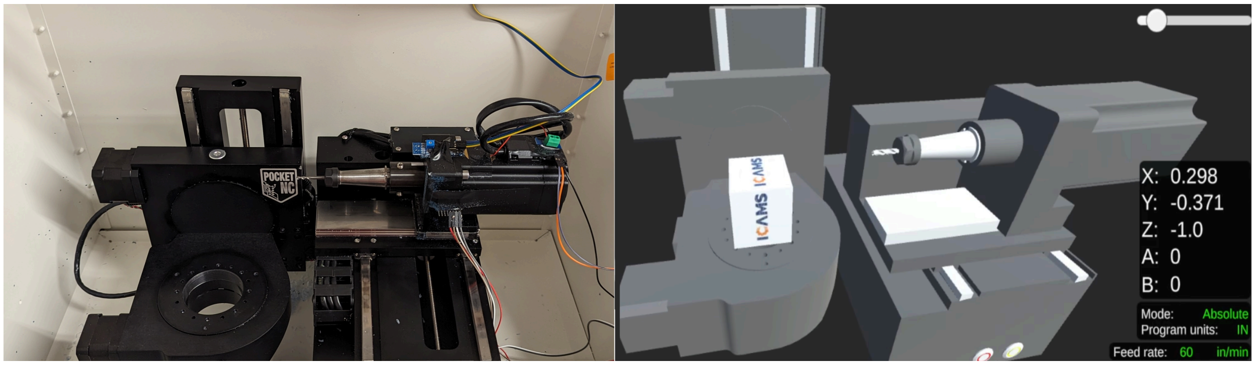

Figure 3: Left: Pocket NC V2-10. Right: Process replication in the virtual domain captured from the Virtual Representation Component (Unity real-time development platform).

support for third-party integration, which can delay efforts to obtain the necessary documentation or technical assistance needed to create the required data infrastructure. Nevertheless, the future looks promising, with interconnectivity and interoperability of industrial equipment improving over the years.

Machine data are used in online real-time simulation for process replication and monitoring of the manufacturing asset. We define process replication as the DTE's near-real or real-time capability to reflect the physical system's state and properties. Process replication starts with creating a virtual model of the physical system, which is imported into Unity. The characteristics and properties of physical domain elements are matched to those of the virtual elements. The model's constants are populated based on measurements in the physical domain. For instance, the machine's dimensions and the maximum travel of the axes are measured and transferred to virtual space. Next, we identify the dynamic variables of

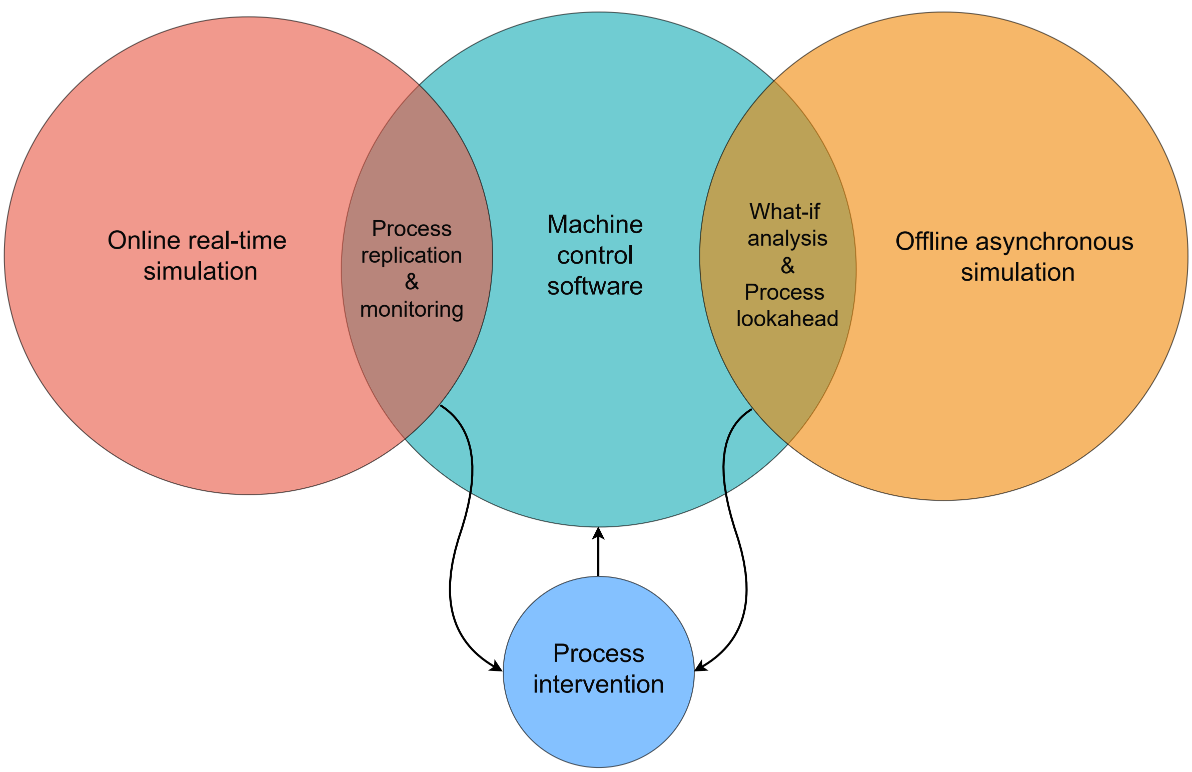

Figure 4: DTE capabilities enabled by different simulation workflows.

interest in the physical system. This step considers documenting variables that change while the machine is in operation, which is an exploratory process. Such variables could include the state of the machine, the position of the axes, the configured feed rate, the revolutions per minute of the spindle, the state of interlocks, sensor values (temperature, pressure, etc.), and other machine-specific variables.

On runtime, the virtual system's state is updated and synchronized based on the readings of the dynamic variables to keep pace with the execution of the physical process. The synchronization polling rate depends on the available computing resources and the requirements of the application. One could describe process replication as an online real-time deterministic simulation of the physical system. This differs from traditional simulation workflows since the inputs are real-time data from the machine control software. More specifically, the inputs of the simulation model are the dynamic variables of interest (i.e., the process variables that change while the machine is in operation). The model then synchronizes the virtual replica with the physical system. As such, the model's outputs are the updated process variables, which reflect the new state of the virtual system. The simulation model is validated via statistical testing, which ensures that no significant difference is observed between the physical and the virtual system's process variables. The online simulation workflow does not include stochastic components since its purpose is to reflect the physical domain properties in virtual space.

Offline asynchronous simulation refers to simulating the machining process without relying on real-time data flows. The model's inputs are not machine data but a preprocessed G-code file with instructions, and the machine's configuration settings. The preprocessed G-code file is parsed and rearranged into a set of commands. These commands are passed to a custom G-code interpreter, written in C#. To ensure that the G-code interpreter works correctly, we have implemented a coordinate monitoring system that maps virtual space coordinates to the corresponding physical space ones. The mapped coordinates are then compared to the G-code file to ensure that the interpretation is accurate. The model's outputs are the process variables that comprise the state of the virtual system. Currently, the offline simulation workflow does not include stochastic components. This DTE capability could be used for "what-if" analysis to explore different manufacturing scenarios. Notably, we have utilized the DTE's offline simulation capabilities to predict collisions caused by commands in the loaded G-code file. By utilizing Unity's built-in physics engine, we are also able to pinpoint the colliding parts. Readers can observe this DTE functionality in our collision detection demo (demo 3. 2024). Finally, using offline asynchronous simulation, the state of the manufacturing asset after executing each instruction could be stored for the generation of reports with a complete, in-depth machine state timeline.

Offline simulation can take place during or outside manufacturing operations. If offline asynchronous simulation takes place while the machine is in operation, the DTE gains lookahead capabilities. We refer to process lookahead as the capacity of the DTE to partially or fully simulate what will happen within a certain time horizon in the future. This includes but is not limited to simulating the effect of subsequent G-code commands. Another promising aspect of combining the simulation modes is the improvement of simulation results by incorporating real-time sensing data in the offline simulation workflow. Sensing data flows could help fine-tune the simulation insight and better predict future states. We are currently working on incorporating more process lookahead functionalities within the DTE and documenting their benefits.

Process replication and monitoring could be combined with process lookahead to enable timely intervention. The idea is that the DTE could prevent a deviation from the nominal operation by predicting it before it takes place and prescribing corrective action. By continuously comparing the actual machining state with the predicted state from the offline simulation, the DTE could anticipate outcomes and adjust the machining strategy in real time. For instance, if a collision is detected later in the machining process, the DTE could issue a machine stop command to prevent further execution of the loaded program. Such an action would result in safer operations, cost savings, and overall productivity increase since a potentially lengthy machine breakdown would have been prevented.

5 CONCLUSIONS & FUTURE WORK

This work considered a generic Digital Twin Ecosystem (DTE) for Computer Numerical Control (CNC) manufacturing processes. The DTE architecture was discussed, and its components were detailed. Two different case studies were presented to demonstrate the DTE's universal applicability in CNC manufacturing processes. The DTE offers two operation modes: i) the real-time process replication mode and ii) the offline asynchronous G-code simulation mode. We described the purpose of these modes and how their combination enables process lookahead capabilities and timely autonomous process intervention.

We believe that harnessing the power of different simulation workflows is fundamental to unlocking the full potential of DTs in manufacturing. Online simulation enables accurate monitoring, real-time analytics, and remote management. Offline simulation allows for comprehensive testing of scenarios and identification of optimal process parameters. The combination of online with offline simulation enables process lookahead, which allows for the generation of predictive insight for better decision-making and improved control. Subsequently, process lookahead paves the way for advanced DTs, which can autonomously intervene in the manufacturing process, dynamically optimize machining parameters, and achieve sustainable improvements in performance and profitability. Simulation-driven DTs can empower manufacturers streamline workflows, reduce downtime, minimize expenses, and optimize maintenance schedules, improving overall operational efficiency. These benefits could significantly help manufacturers gain a competitive edge in rapidly evolving industrial landscapes. As DT technologies continue to evolve and integrate with advanced simulation capabilities, they will become indispensable tools for driving continuous improvement and shaping the future of smart manufacturing.

Future work considers exploring how the unified simulation capabilities of the DTE can help improve decision-making and enhance overall manufacturing productivity and efficiency. Firstly, we will identify and document the benefits of combining real-time process replication with offline asynchronous simulation. Next, we plan to investigate how process lookahead can be utilized to identify hazards, errors, and deviations in machining process. An important consideration at this step is understanding the computational requirements of process lookahead, and its limitations. For instance, an interesting challenge would be to identify how far into the future of the manufacturing process the DTE can simulate without causing synchronization issues with the physical asset. Furthermore, we plan to explore how process lookahead can be improved by combining offline simulation insight with real-time sensor data flows. Finally, we plan to demonstrate how different simulation workflows enable cognitive DTE capabilities for improved decision-making and autonomous process intervention in realistic manufacturing scenarios.

Another future research direction is investigating ways of interaction with the DTE, focusing on Extended Reality (XR). Using XR, one can display real-time data and analytics on equipment using head-mounted displays or handheld devices, allowing operators to view machine status, performance metrics, and diagnostics without diverting their attention from the manufacturing process. The interactive features of XR tools give operators quick and intuitive access to essential process information, improving their ability to carry out complex tasks accurately and effectively. Finally, the networking capabilities of modern XR devices enable collaboration across teams and individuals while also allowing for remote educational opportunities.

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