Data-Driven Digital Twin For Data Management And Decision Making In Digital Factory

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***Abstract*—Developing a fully-fledged, data-driven digital twin of a production line involves several challenges related to data quality, data integration, and real-time simulation of models from different dynamic systems. This PhD research aims to leverage digital twin (DT) technologies to address these challenges and create data-driven digital twin of a production line. Our preliminary activities focus on conducting an extensive literature review to build theoretical foundations and exploring a Functional Mock-up interface standard for integrating different models into a single simulation environment. Additionally, we present some preliminary results, which include a dataset of real-time production parameters obtained from the additive and subtractive manufacturing processes.**

I. Introduction

A digital twin is a virtual representation of a physical system or production plant, capable of simulating and replicating the behavior of manufacturing operations in a virtual environment, preventing equipment failures, enhancing efficiency, and improving the quality of part production [1]. By creating a digital twin, manufacturing industries can test various scenarios to optimize decision-making and reduce maintenance costs through predictive maintenance and anomaly detection [2]. As described in Figure 1, this PhD research aims to develop a data-driven predictive digital twin using machine learning and the FMI Standard. The digital twin will be able to simulate the real-time behavior of the production plant, ensuring maximum product efficiency and reducing maintenance costs by enabling predictive maintenance (PM) and anomaly detection algorithms. Building a data-driven digital twin is a complicated task, as it involves several challenges that need to be addressed to develop a fully-fledged digital twin for a digital factory. The challenges includes:

II. Challenges in Digital Twin Implementation

*A. **Difference Between Digital Twin And Digital Shadow:** To model a digital twin of a production plant, it is essential to have a clear objective and a correct understanding of the definitions of both "digital twin" and "digital shadow." These are distinct terminologies, and it is crucial to understand the differences between them before developing a digital twin.*

Digital Shadow: Represents the current state of the physical system with one-way communication between the physical and virtual models.

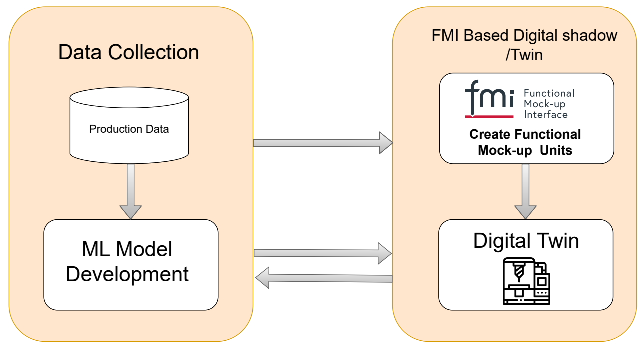

Figure 1: Data Driven Digital Twin.

Digital Twin: A DT not only mirrors the current state but also incorporates simulation, predictive analytics, and decision-making capabilities with bidirectional communication between the physical and digital twins [3].

*B. **Data Quality**: Smart manufacturing industries generate a vast amount of data [4], from multiple sources, such as sensor readings and historical records, which may include noise and missing values. Therefore, it is essential to validate and apply data pre-processing techniques.*

*C. **Data Integration**: Creating models to build digital twin requires data from multiple sources [4], including sensor readings, historical databases, etc. Integrating such diverse and heterogeneous data sources into a single unified model is a complex task therefore it is essential to developed techniques that allows to integrate these diverse data sources and facilitate the development of data driven Digital Twin (DT).*

*D. **Real-Time Simulation**: The digital twin of a production plant includes various models representing the plant's individual components [5]. Each model is built using different tools and software and has its own data formats and computational requirements, which requires the seamless integration of these models by setting up a co-simulation environment to achieve complete system simulation.*

III. Ongoing Activities

The current research activities focus on exploiting DT technologies and addressing the challenges of developing a fully-fledged digital twin for the production line. We are currently working on collecting real-time production data from additive and subtractive manufacturing operations to optimize manufacturing operations and production recipe parameters. Additionally, we are also exploring the Functional Mock-up interface standard to create a dynamic digital shadow of our production plant. This digital shadow simulates the plant's real-time behavior, allowing us to collect more manufacturing data. We use this data to build high-fidelity machine-learning models. By creating Functional Mock-up Units, these models enable the setup of a co-simulation environment, which is essential for creating a digital twin of the production plant.

IV. Preliminary Results

In the first months of the project, we created a dataset by collecting real-time production data from additive and subtractive manufacturing processes [6]. The dataset is collected in the Industrial Computer Engineering (ICE) laboratory: a research facility [7] at the University of Verona equipped with a fully-fledged production line, assembled by using real-world machinery connected by a sophisticated communication and data collection architecture based on the OPC Unified Architecture (OPC UA) standard, connecting all the machines to the Advanced Manufacturing Controller (AMC) [8]. The dataset includes real-time production parameters obtained during the additive and subtractive manufacturing processes. This includes 3D printing parameters, G-code parameters (e.g., hole diameter, cutting depth, spindle speed) used for milling the workpiece. We processed workpieces consisting of rectangular cuboid shapes with different configurations, materials and production parameters, as reported in Table I. Each workpiece is assigned an ID ranging from 0 to 30 and is created using different combinations of materials, infill levels, patterns, spindle speeds, and feed rates. Varying infill levels and pattern combinations are used to produce workpieces with different structural and thermal properties. Moreover, different spindle speeds and feed rate combinations are used to reduce the time taken to process the workpieces and the heat generated during the process.

Table I: Dataset Description

Parameter	Values	Description
ID	1-30	Identifier of the workpiece
Material	PLA, PETG, Polycarbonate, ABS, Nylon, Carbon Fiber	Material used to print the workpiece
Infill Level	15, 30, 50	Infill percentage of the workpiece
Infill Pattern	Rectilinear	Internal infill structure of the workpiece
Spindle speed (RPM)	200, 250, 280, 300, 350, 400	Velocity of the spindle during the milling processing
Feed Rate (mm/min)	50, 100, 150, 220, 270	Speed at which the cutter engages the workpiece
Cutting Depth (mm)	9	Depth of the holes
Hole Diameter (mm)	4	Diameter of the holes

V. Conclusion And Future work

In the future, we plan to extend the dataset by applying additional manufacturing operations from the ICE production line. We also aim to explore AI-based modeling techniques to build predictive machine-learning models that can analyze historical and real-time data to predict potential maintenance requirements, anticipate failures, and optimize performances. These models will be used to create dynamic digital shadows of the production line and further develop into a fully-fledged digital twin using advanced real-time data integration techniques. For the final thesis, we aim to combine all these dynamic models generated into a single simulation environment using the Functional Mock-Up interface standard to achieve complete system simulation. Additionally, we will explore data management and visualization tools or software to build dynamic and interactive dashboards for monitoring and interacting with the digital twin model. The final phase of the PhD thesis involves scalability analysis and at-scale validation which aims to enhance and optimize our digital twin model performance, by simulating and anticipating different operational scenarios, it involves validation of the model through co-relation between experimental data and the simulated data, creating a simulation scenarios to mimic the real world conditions and predict the model's behavior accurately. By conducting this scalability analysis and validation, we ensure the reliability and accuracy of digital twin predictive capabilities and real-time analysis and the final outcome of the digital twin model is align with our actual research objective.

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