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Digital twin frameworks for improved handling of soft and deformable products in food manufacturing

Matteo Iacovanelli1*, Giovanni Mazzuto1, Marco Ortenzi1, Filippo Emanuele Ciarapica1, Maurizio Bevilacqua1, Marco Rossi2
1 Departement of Industrial Engineering and Mathematical Sciences, Università Politecnica delle Marche, Ancona, Italy
2 R&D department, B2A s.r.l., Trento, Italy

Abstract — The automation of grading, handling and packaging of soft and deformable food products in the industry necessitates precision in manipulation, adaptive gripping, and real-time monitoring to ensure uniform quality and prevent damage. These aspects are the objectives of the European project AGILEHAND. This project aims at developing advanced technologies as a strategic instrument to improve flexibility, agility and reconfigurability of production and logistic systems of the manufacturing companies. In this context, this paper discusses the development of a data-driven framework for automated generation of simulation models fro the realization of the digital twins in food factories. The core of this framework involves discrete event simulation: by real system data it is possible to streamline the reconfiguration of production and logistic systems. During this process, it is also possible to promptly identify design or process sequence problems at an early stage through cross-domain simulation. Firstly, this framework supports the project manager in scheduling production by optimising resources and minimising the order of Estimated Time of Arrival. Then, during the system monitoring phase, it simulates new scenario to find the proper corrective action when a significant deviation from the plan occurs. In the end, the accurate capture of dynamics arising in the physical layer allows an effective evaluation of their negative effects on the system's overall operational state. This approach supports informed decision-making in planning and controlling logistics, production, and associated activities, providing a comprehensive framework for enhanced operational efficiency.

Keywords— Digital Twin, framework, data-driven, food industry, Artificial Intelligent

INTRODUCTION

Many products in the real world are deformable and can easily change shape while someone is manipulating them and, in most cases, do not have a rigid composition. This is particularly evident in the fresh market where the companies' essential aim is to produce a broad range of low-cost, high-quality products with short lead-times in varying lot sizes, with environmentally friendly production and built to individual customer specifications [1]. In particular, challenges in the fresh produce sector persist, with substantial losses and waste occurring from farm to consumer, reaching significant percentages [2]. The intricacies of these challenges become even more pronounced in mixed-model production systems, where the execution flow diverts dynamically due to custom orders, fluctuations in demand, faults, quality-control, and product rework. In such dynamic conditions, the need arises for the reallocation and reconfiguration of production resources, redirection of production flows or re-scheduling of orders [3]. This adaptive responsiveness is crucial to ensuring efficiency and minimizing losses in a production environment marked by variability and customization demands.

However, digital service innovation is highly challenging because production plants often do not communicate with the internal logistics handling system in a timely manner. This lack of timeliness does not make the production system agile, especially in contexts where a variety of products with a short life cycle have to be handled [4]. In this context, AGILEHAND aims to develop advanced technologies for grading, handling and packaging autonomously soft and deformable products, as a strategic instrument to improve flexibility, agility and reconfigurability of production and logistic systems of the European manufacturing companies. In particular, the project uses the Digital Twin (DT) and a set of Artificial Intelligence (AI) based solution that will allow for monitoring, adaptive control and synchronisation of production and logistics flows in a factory, even when faced with a variability of products, production mix or fresh market, guaranteeing high performance in customer response time, and an efficient use of resources.

In fact, a DT is a virtual representation of an object or system, connected to it throughout its lifecycle. DT effortlessly integrates historical and real-time data sourced from physical systems with sophisticated physics-based models and advanced analytics, all facilitated by predictive models generated by AI algorithms. This fusion results in the development of digital replicas characterized by high integrity, awareness, and adaptability, empowering manufacturing entities with predictive services [5]. In the past, DTs have usually been built from scratch and were strongly tied to the system they replicate. Nonetheless, as the popularity of DTs has grown in the last years the demand for rapid development of complex, reliable, and scalable DTs increased significantly. DT frameworks have been proposed and implemented to deal with such requests [6]. The DT framework aims at providing a holistic system visibility and a flexible decision-making process to achieve the necessary responsiveness of the reconfigurable manufacturing system and improve its performance during its operation phase by continuously collecting real-time data from its components. Then, this data can be stored, processed and analysed using information analysis as well as simulation and optimization module blocks.

Based on the above ideas, DTs can quickly provide critical decisions, such as the appropriate configuration of the reconfigurable manufacturing system, to effectively deal with sudden changes in a globally competitive market [7].

The Reference Architectural Model Industry 4.0 (RAMI 4.0) architecture serves as the reference architecture model for Industry 4.0, offering a framework for the digital transformation of manufacturing facilities. Utilizing this framework, various aspects of DT can be systematically organized. Defined in DIN SPEC 91345, RAMI 4.0 adopts a layered cubic model, with dimensions representing the architecture of assets, their life cycle, and their hierarchical assignment. This three-dimensional layered model is designed for optimal utilization. Each layer delineates the assets based on their respective tasks or functions. These categories include classification in business processes, asset function, information, communication, and integration of physical assets into the virtual realm [8], [9].

Not all levels need to be utilized in every instance. For this reason, Gil et all. [10] assessed criteria in the field of DTs and went deeper to explore functionalities, practicalities, and capabilities of some of the tools. It examined, categorized, and discussed details related to the anticipated features that a DT should possess and the essential elements this framework should offer. This last aspect includes the limitations of high-fidelity integrated models and the limited coverage of common features for DTs.

Nicoletti et all. [11] present functional and technical frameworks for applying DTs. They propose a conceptual 3-D framework of DT by listing its constituent components (physical space, physical entity and virtual space), further to this they explain how important the links between physical and virtual entities are. This concept is echoed by [12], indeed they expanded the 3-D framework into five dimensions (5-D), thus, introduced two more dimensions, namely, data and service. The 5-D approach allows real-time control of the plant, enabling instant intervention in case of issues, and simulating future scenarios to adapt decision. The result is a timely, bidirectional, long-term data linkage between a physical entity and its virtual counterparts.

A further step was developed by Zhang et all. [13]. They propose a 5-D model-driven reconfigurable DT system framework with a reconfigurable strategy. It saves time in reconfiguring virtual manufacturing systems and reduces the cost of system reconfiguration verification.

Once given a description of the components of the DT framework, Autiosalo et all. [14] describe the autonomous software entity capable of connectivity with others. These DT functionalities are situated in distinct systems, necessitating data interfaces among them.

Taking into consideration the various structures of the DT frameworks analysed in the literature review, this paper describes the development of a DT based on models extracted, via AI, from real system data. This DT will make it possible to simulate, plan and synchronise the production and logistics of a system during line reconfiguration. The DT solution will support the decision-making in the planning and control of logistics, production and related activities. The implementation of DT also brings improvements at the level of lean manufacturing, as better production management allows for optimizations in terms of raw materials and waste reduction as well [15]. The novelty of the proposed framework is in the data-driven approach that exploits advancements in machine learning (ML) and process mining techniques, as well as continuous model improvement and validation.

The present work is organised as follows. Section 2 defines the DT scope for the AGILEHAND project, detailing the modules comprising the DT framework and their interconnections for implementing digital twin functionality.

Section 3 focuses on providing descriptions of the framework components, highlighting the functionality developed by each one. Section 4 describes the modelling of the real physical environment using discrete-event simulation. Section 5 illustrates how integrating DT with AI and ML, guided by human expertise, elevates operational intelligence, enabling effortless data exchange and skill refinement. Finally, the conclusions of the work are reported in Section 6.

THE AGILEHAND DIGITAL TWIN

The Digital Twin scope

The DT is a new tool for the Production Manager, able to predict how to optimise resources, simulate the production outcome, and update the Estimated Time of Arrival (ETA) during production.

The Digital Twin explained using use case diagram

Below is a diagram illustrating a use case of the Digital Twin.

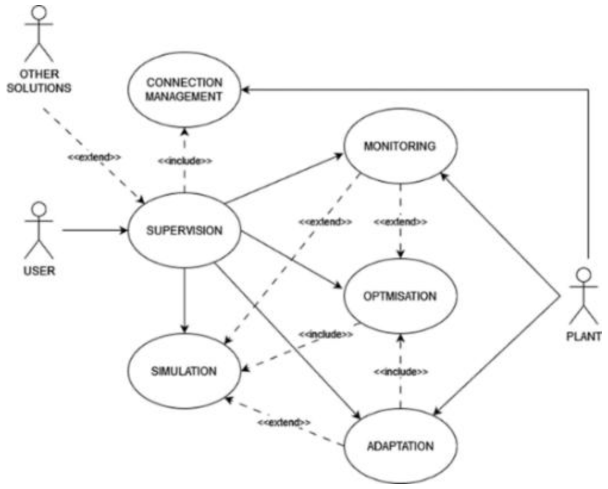

Figure 1 Digital Twin framework.

The DT framework offers a comprehensive insight into the development of DTs, providing a detailed understanding of their functionality. It consists of multiple interconnected modules, each serving a specific purpose in the system lifecycle, as illustrated in Figure 1. DT enables real-time Monitoring, Simulation, Optimization, and control of physical elements, enhancing operational efficiency and decision-making capabilities [5].

The Supervision module facilitates real-time monitoring, management, and coordination of the actual system components. It coordinates the information management, decides operation timings, issues commands, and synchronizes event flow. Thus, the system can allow the real-time data analysis to review and make informed decision, execute control commands, generate alerts, data collection.

To achieve these goals, the Supervision module requires a connection with the physical plant, so a Connection Management module is compulsory. Therefore, the Connection Management module provides all the necessary functionalities to manage a reliable and secure connection between the DT and the actual physical system to enable real-time monitoring, control, and general interaction.

Once the connection between user and system is established, various functions become accessible such as the Simulation module that is the most important one in the proposed DT. The Simulation module entails leveraging the DT simulation capabilities to reproduce the behaviour and performance of the physical system so as to emulate different scenarios without impacting the actual physical system.

The Monitoring module is an extension of the simulation one that receives data and parameters directly from it. Monitoring module continuously oversees and manages the physical plant or system by utilizing real-time data and insights provided by the DT: this ensures the efficiency and alignment of plant operations with predefined parameters and targets. In addition, it acts as a bridge between the DT and the actual system. Real-time data collection is an inherent part of the process, where Monitoring module consistently gathers data from the physical plant, capturing various parameters and performance metrics. Subsequently, the collected data undergoes analysis within the Supervision module to identify trends, anomalies, and deviations from expected operational parameters.

In this context, significant relevance is assumed by the Optimisation module. It involves real-time and near real-time optimization of production line operational variables to maximize efficiency, quality and resource allocation while minimizing waste and operational costs. It receives data directly from the sensors positioned along the production line. The operator, through the Supervision module, works directly to change the production line parameters suggested by the optimization module. Specifically, it aims enhancing the performance of the actual system through Simulations module and adjustments of various parameters.

Finally, the last module is the Adaptation, directly connected to the plant. It involves dynamically adjusting the actual system based on Optimization module recommendations and results. This process allows for real-time modifications to the production line and its operational variables, aiming to enhance efficiency, quality, and resource allocation while minimizing waste and operational costs.

It is important to highlight that Optimisation and Adaptation module are strictly connected. In fact, Optimisation module evaluates results from the Simulation module and the plant Monitoring module to identify potential improvements, bottlenecks, or inefficiencies in the production line; then, the Adaptation module can receive recommendations to be implemented. In particular, the user can choose to implement them, applying adjusted parameters to the production line for improved efficiency or the system dynamically implements them on the production line, and modifies the simulation model, accordingly, operating completely autonomously.

DIGITAL TWIN ARCHITECTURE

The Digital Twin components

The component of the DT comprises fundamental building blocks that play distinct roles, addressing a diverse range of requirements and scenarios: physical devices, software on a desktop PC (Native), functions in a On-Premises data centre, and functions in the cloud [16]

Figure 2 describes the integration across diverse components of the DT infrastructure.

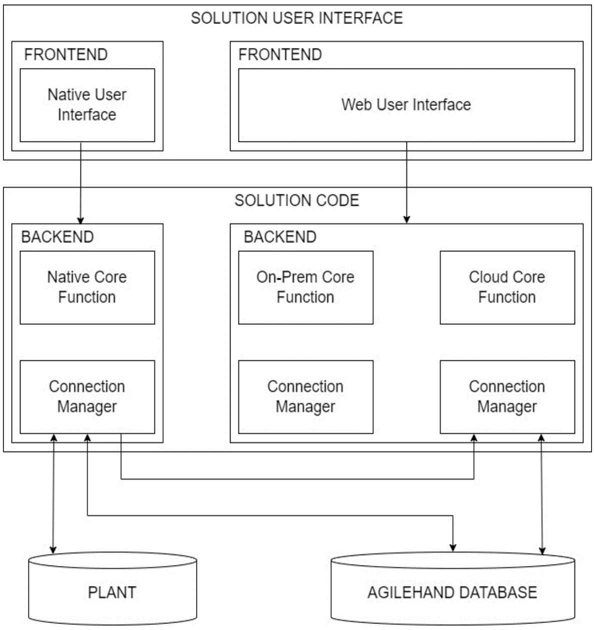

Figure 2 Digital Twin components

Specifically, physical devices are responsible for data collection, monitoring, and interaction with the environment. Native components are software elements designed to work on a local PC connected directly to the plant. It provides a user interface that enables access to local resources, real-time data processing, and low-latency operations. On-Premises component is an app or Web site located on a company-internal server (intranet), gives organizations direct control over their infrastructure and data. On-Premises functions may include data storage, databases, authentication services, or other applications that are not suitable for the cloud or need to be tightly integrated with physical devices [17].

The last one is the Cloud Component, as with on-prem the cloud is also an app or website but residing in remote data centres managed by cloud service providers. Cloud components excel in tasks demanding significant computational power, extensive data storage, and seamless scalability to meet varying demands.

Frontend and Backend Components

Once all the components are listed, the focus is on ensuring the autonomy of each solution, allowing them to be deployed independently, while concurrently fostering their integration into a cohesive system.

First of all, it is important to distinguish between frontend and backend components. A frontend component is the user-visible part of the solution program to be used by the user to interact with the system, e.g. the User Interface (UI). The UI is fundamental to the way individuals interact with software and the data it manages [18]. As is represented in Figure 2, it was chosen to have two types of UI. The Native UI provides a graphic user interface, it is optimized for the device it resides on, offering a seamless and responsive interaction between the user and the plant.

Similarly, also Web UI provides a graphic user interface but that acts as a universal access point, allowing access and use of software features.

On the other hand, the backend refers to the part of an application or system that handles functions not visible to end users. It is responsible for processing data, business logic, and interaction with the database. Essentially, it constitutes the "engine" of the application, these core functions encapsulate the essential operations that contribute to the effectiveness of the overall system. The main functions in turn are subdivided according to whether the component is internal or external.

Internal Backend Components, related to native components and on-premises components, handling critical aspects such as business logic, data processing, and decision-making algorithms. In native components, all modules of the DT are operational, whereas in on-premises components, the Adaptation module is not functional.

In Externally Available Backend Components, related to cloud components, the function of DT is limited, the modules that can be used are the Optimization and connection and data manager.

Connection types

The digital twin optimizes data exchange and collaboration between its virtual representation and physical counterpart, facilitated by digital transmission protocols [19]. The other part of the backend is the Connection Manager. It is an internal application/software within the company that facilitates the transfer of data between various developed applications (Native, On-Premises and Cloud) of the company and enables the output of this data to an external database (AGILEHAND Database). It's important for the MQTT protocol to include flexible mechanisms and integration modules based on decoupling. This approach ensuring compatibility, and seamless integration with existing IT infrastructure and production systems. This contains the functionality related to solution connectivity with external entities, other solutions, and devices. This class encompasses the mechanisms through which the solution seamlessly integrates with other components of the software ecosystem, facilitating an exchange of data and insights.

Figure 3 shows the connection between the Native components with the external entities.

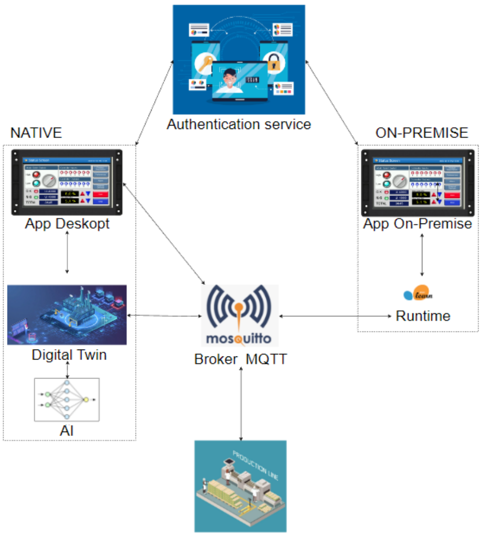

Figure 3 Digital Twin connection

Database system

Comprehensive data management in the entirety AGILEHAND solutions resides in the Data Integration Layer, tailored to handle diverse data types. It offers indispensable services that encompass data persistence, retrieval, and near real-time processing. In particular, the Data Integration Layer is categorized into specific services providing several database services meticulously adapted to the distinct data requirements of various AGILEHAND solutions. This multi-database strategy empowers each solution to choose the most fitting storage mechanism for its unique data needs.

To handle the diverse type of data, data services encompass three different Database. Relational Database is a type of storage database that provides access to related data points. MySQL / PostgreSQL are types of the databases utilized that allows to represent data in tables. Timescale is a Time-Series Database optimized for storing and serving time series through associated pairs of times and values. The file storage service is a high-performance distributed object storage system designed for extensive data storage. In these terms, Minio finds utility in storing unstructured data such as photos, videos, log files, backups, or software packages.

SIMULATION AND MODELLING

Developing models within the DT ecosystem is undertaken with the objective of faithfully reproducing the behaviour of the physical plant. To obtain this objective, the Discrete Event Simulation (DES) technique was chosen during the system modelling phase, aligning with the company's physical structure. This method conceptualizes mobile objects in the production line as entities in DES, each possessing unique attributes. Operators are portrayed as renewable resources, transitioning between idle and active states based on events, while items are modelled as non-renewable resources.

The digital model was developed using Python with the Simpy library, providing necessary tools for discrete event digital modelling and adhering to object-oriented programming principles. In Simpy, it is utilized a class to collect simulation data, stored in an empty list. This encompasses time-related information like entry and exit times from a station, process start and end times, facilitating the calculation of waiting and processing times. Details such as entity type, ID, additional data, and company-specified thresholds are also recorded. Consequently, the subsequent phase involved modelling system components, including stations, resources, and entities.

The primary function of a station within this system is like a storage, where users can define how stations hold entities. Entities are received and sent to other stations, as specified in the input and output attributes of the “Station" class. Stations can perform tasks using operators (renewable resources) and may require non-renewable resources like raw materials. Specialized stations in the system have unique roles.

The real system involves moving objects, requiring accurate representation in the model. Entities, encapsulating common attributes, are structured under the Entity base class. This classification enables the identification of each entity's nature, associated production order, and quality level, defined by the company's historical data in a specific class method.

A similar modelling approach is applied to represent production line operators. The "Operator" class is designed to define the standard operator, characterized by specific attributes such as individual skills and assigned workstations. These advanced features are essential to replicate the dynamic structure of the real production environment in the digital model.

ARTIFICIAL INTELLIGENCE AND DIGITAL TWIN

The integration of DT technology with AI and ML, informed by human knowledge, introduces a higher level of intelligent operations, the digital triplet. This integration enhances analysis, decision-making, and execution by leveraging human comprehension of technological advancements. [19].

Therefore, the concept of the digital triplet necessitates a structure consisting of four levels of DTs: sophisticated decision-making processes driven by ML infused with human intelligence and creativity, predictive and emulative control of physical system behaviours, maturity attained through iterative real-time observation of physical system behaviours, and a layer dedicated to visualizing and simulating virtual attributes. This hierarchical approach elucidates intelligent manoeuvres, thereby fostering the facilitation of the exchange of data and information across digital realms, physical environments, and human entities. Through astute actions, the DT fosters seamless integration between humans and machines while catalysing skill evolution [20].

However, as analysed by Mazzuto et all. [21], the transformation of monitored parameters provided by physical sensor data into information represented as indicators is fundamental. The potential benefits include not only the reduction of the quantity of data examined but also the maximization of useful information content.

In this context, the proposed framework uses a data-driven approach that takes advantage of advances in ML and process mining techniques, as well as continuous model improvement and validation. Indeed, the term ML refers to the construction of algorithms that learn through data and thus ML is necessarily data-driven. The integration of data-driven DT with production monitoring methods and scheduling optimization tools enables ensuring the actions that should be undertaken initially to bring significant benefits to the process: having a clearer representation of its limitations or criticalities ensures better awareness during the planning and control phases [22]. For this reason, the AGILEHAND project develops a reconfigurable intelligent machine with the capability to autonomously adapt, possessing the intelligence to discern when and what alterations are necessary. Utilizing learning methods, upon receiving a new order, the system can dynamically redistribute resources and autonomously revise the entire production schedule, effectively ensuring the fulfilment of delivery deadlines. This marks a progression in the maturity of cyber-physical systems, evolving from fundamental functionality to analytical comprehension, decision support, and ultimately self-optimization.

DISCUSSION AND CONCLUSION

The paper presents an approach to managing soft and deformable food products using the DT to optimize production and logistics in food factories, offering significant potential to improve operational efficiency and product quality.

From the end-user perspective, the positive aspects include increased flexibility, agility, and reconfigurability in production systems. Through real-time simulation and monitoring, it is possible to plan and control production optimally, allowing for a rapid response to changes in demand and efficient resource management, significantly enhancing the company's dynamic adaptation capability.

The integration of Machine Learning technologies and the use of real-time data for simulation provide robust decision-making support, enabling more accurate planning and control of production activities. This approach also promotes sustainability by reducing waste and energy consumption.

However, some challenges may arise, such as the complexity in integrating existing systems with the new framework and the need for specialized skills to manage the DT. The implementation and management of the framework may create significant challenges for end users, especially if they are unfamiliar with AI and simulation technologies.

A future improvement could involve the development of more intuitive user interfaces and dedicated training programs for operators, aiming to facilitate the effective use of this advanced technology. Furthermore, AI could be utilized not only for continuous improvement of process analysis and optimization but also to manage the interaction between operators and DT in a simpler and more intuitive manner, even with non-specialized operators. For example, with a graphical UI driven by speech recognition, capable of interacting with operators in a conversational mode, both for input and results.

Moreover, it is important to note that if the DT is used with batch data instead of real-time data, it can still produce accurate results, but they may prove to be inadequate or already outdated compared to the highly dynamic reality of production lines. Indeed, the handling, storage, and transportation conditions can vary significantly and rapidly due to environmental factors, product maturity, and logistical variables for products highly susceptible to damage and quality degradation. Using real-time data for the DT is essential. This enables it to effectively take over the role of the production manager, especially for products highly susceptible to damage and quality degradation. In conclusion, the use of real-time data in the DT framework represents a significant step towards more effective management of soft and deformable food products. This technology provides a level of precision and adaptability that exceeds traditional human capabilities. This technological advantage makes the DT not only a tool for process optimization but a necessary component to ensure product quality and economic sustainability, in the highly competitive food production industry.

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