MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 34 Issue 2, July-Dec 2024, Pages: 1202-1218

Digital Twins in Paint Manufacturing: Data Engineering Approaches for Process Optimization

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Abstract

Digital twins are virtual replicas of a physical entity. A digital twin can mimic the properties of its physical counterpart. Factors such as data fidelity, availability, and the required refresh rates are crucial considerations that provide the mapping between the digital and physical entities. In this chapter, we explore the concept of digital twins, their underlying philosophies, implementation strategies around data engineering foundations relevant to paint manufacturing, as well as their implications for process optimization. The importance of engineering the flow of existing and novel data sources to populate digital twins that enhance optimization techniques is a consistent theme throughout the chapter. We use paint manufacturing as a representative application area throughout the chapter. Paints are multicomponent fluid systems whose rheology is a predictor of many important properties such as printability, scrub resistance, and anti-corrosion properties. We argue that digital twins are a key enabler that allows the incorporation of closed-loop optimization techniques to ensure that there is always a mapped control action based on physical measurements, that signals the appropriate actuators to drive the paint-making process towards its optimal setpoints. Such control actions direct the system bots towards achieving the realized optimal paint solution when there is a client toleranced deviation in paint property, based on process flow recommendations made by the digital twin. The chapter describes how data ledging of the past data generated from the lab, pilot, and production equipment as well as the recommendation-based deployment of the digital twins can augment and work seamlessly with both existing empirical models as well as mechanistic understanding of the paint-making process leading to a significant gain in property realizations. We also discuss the potential transformation in process optimization in how companies operate, as they move from traditional thermal systems of risk assessment for business decisions towards a digital economy where there is constant vigilance of optimization in every stage of the asset lifecycle.

Keywords: Digital Twins, Virtual Replicas, Data Fidelity, Data Availability, Refresh Rates, Process Optimization, Paint Manufacturing, Rheology, Printability, Scrub Resistance, Anti-Corrosion Properties, Closed-Loop Optimization, Control Actions, Actuators, System Bots, Process Flow Recommendations, Data Logging, Empirical Models, Mechanistic Models, Property Realization, Digital Economy, Asset Lifecycle.

1. Introduction

Digital Twins (DTs) are creating tremendous hype around their use in modifying the behavior of physical systems, especially for optimization or automatization purposes. A great number of technical publications and even some standards are surfacing in the Digital Twin area, defining concepts and vouching for this technology as the hottest one in this Fourth Industrial Revolution. The expectation is that the results from these Digital Twin platforms be used along the life-cycle of physical systems, not only during the operational moment, but also during the phases of conception and design, construction and assembly, planning and monitoring, and maintenance.

Era-5 is the next main upgrade of the Industry 4.0 architecture, comprising a list of new advanced technologies that include Digital Twins, Artificial Intelligence, Blockchain, Cyber-Physical Systems, and Next-Generation Systems, Workloads, and Application Platforms. These advanced technologies can be viewed as a technological portfolio that will allow enterprises to change themselves toward becoming True Smart Enterprises – an enterprise that has vertically and horizontally aligned the various functions of its business, a customer-centric philosophy, a data-driven culture, and invested in the technologies required for their digital transformation.

There are several examples of applying Digital Twins in the different phases of the typical lifecycle of a manufacturing operation (or enterprise), usually trying to improve the operational performance by embedding advanced technologies as great enablers of the True Smart Enterprise concept. However, there is a gap in research involving the development of advanced integrated DT environments and platforms, which could be applied during the conception, design, and assembly phases of the life cycle of manufacturing enterprises.

1.1. Overview of the Study

Digital twin architecture originated from aeronautical and aerospace engineering constraints that demanded the development of reliable techniques to guarantee the operational integrity of their components. A digital twin consists of mapping a physical entity into a virtual object that can accurately simulate its physical counterpart by

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
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integrating the physics underlying the phenomena governing its operation, the data gathered from the physical entity, and the interactions with the environment. From this integration, an asset's digital twin becomes a source of predictive information that can be used to optimize the management of the physical system. Digital twin applicability has grown and spread to several key sectors of our economy. In these last decades, the arena of manufacturing has gained a prominent role in the digital transition initiated with Industry 4.0.

The digital twin development and applicability have been gaining momentum in manufacturing and production processes through enabling technologies such as additive manufacturing, cloud computing, augmented and virtual reality, robotics, artificial intelligence, Internet of Things, 5G networks, etc. One of the key areas is data engineering, which is responsible for the design and development of modern data architectures that enable the integration of production and business processes. This study proposes some data engineering approaches to process modeling, data pipeline development, and process optimization, applied to the paint manufacturing industry. These approaches apply to the architecture capable of implementing a digital factory framework that integrates data from all parts of the production process in one architecture capable of providing tools that allow holistic and organization-wide process optimization insight.

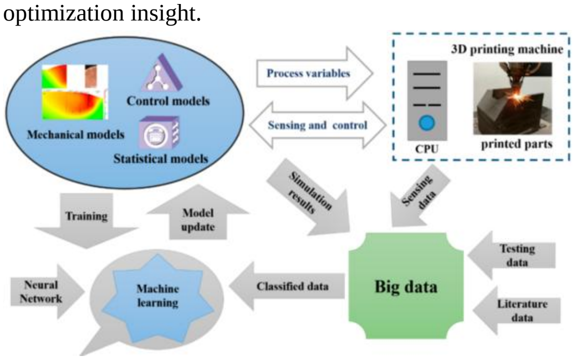

Fig 1 : Digital Twins for Additive Manufacturing

2. Understanding Digital Twins

This section defines the term "Digital Twin" and describes its underlying principles. Next, we provide a historical overview of Digital Twin development, before concluding with an overview of Digital Twin applications in manufacturing.

1. Definition and Concept

The term Digital Twin (DT) describes a digital counterpart of a physical asset or process. A DT can serve various purposes, the most important of which include simulation, prediction, filtering, and versioning. The main purpose of a DT is to improve the understanding and functioning of the asset or process and to inform decision support systems. The term DT has its roots in the field of aerospace engineering, where the initial idea was to develop a high-fidelity model of an aerospace vehicle system that assists with fault detection and prediction during the vehicle's operation. The concept gained significant attention when it was introduced in an industry context during a presentation at a conference on spacecraft in 2010. However, the term had its breakthrough in 2014 when presented as a cornerstone of the Internet of Things by a digital industry business unit.

2. Historical Development

Although the term DT has only gained popularity during the last decade, its roots can be traced back to the field of cyber-physical systems, which describe the convergence of physical and computational processes. Cyber-physical systems essentially consist of physical entities that are represented in the digital realm by models or data ecosystems, which reflect the entities' state and process information. From there, it is only a small leap to DTs that can be used to provide insights into a physical object or process, answer queries on physical states, and generate forecasts. Over-convergence of a DT and its physical counterpart can be achieved by combining it with sensor technology, thereby providing a feedback-loop-based concept that continuously updates and aligns the digital and physical realms. This allows not only for predictions of short- and medium-term future states of the physical object but also for long-term forecasts based on available databases and matching models.

Equation 1 : Real-Time Process Error Function

$$E_p(t) = |Y_{twin}(t) - Y_{real}(t)|$$

Where

$E_p(t)$: Real-Time Prediction Error

$Y_{twin}(t)$: Output from the Digital Twin Model

$Y_{real}(t)$: Actual Process Output at Time t

2.1. Definition and Concept

Introductory Content

A digital twin mirrors the physical counterpart in the virtual world. Moving from traditional data models to digital twins, several systems are now able to immediately recognize and respond to physical systems in the virtual world with the help of highly scalable data modeling, providing data access layers, inference engines, simulation capabilities, and machine learning or AI predictive modeling services that can increase data-driven decision-making capabilities. By doing this, the data technology layers form an intelligence layer that enables humans, and humans merged with machines, to make better real-time decisions.

Definition

There are several definitions of digital twins which include the following. Digital twins are 1:1 representations of physical products or processes at any point in their lifetimes. They contain a dynamic digital model that is continually updated with data from the physical twin. Advances in sensor technologies and the Internet of Things facilitate the easy collection of operational data, making it easier to develop and create digital twins in every industry sector. The main real-world objective is to produce immersive experiences, which can be used for experimentation, design, testing, selection, optimization, maintenance, and support. The definition presented adopts a strategic view drawing on the related concepts of Cyber-Physical Systems which highlights the actions and synergies between the real and the virtual design environment and products. Digital twins are computer-based simulations of physical entities that mimic real-time physical properties, configurations, and behaviors, being continually updated by streaming data coming from sensors embedded in physical products.

2.2. Historical Development

The recently used term "digital twin" relies on a previous concept of "shadow models" and a "virtual representation" of a physical entity, which is a model generating and analyzing real-time data. These two explanations are rather vague and they lay an effort on the virtual components, which are just the means for the final purpose of supporting knowledge and decision on the physical entity (and not its behaviors). The term "digital twin" was used for describing space systems during a period long before the applicability to CGE with associated ICT infrastructures. The fact that its incipient applications are mainly in the aerospace industry and other complex systems places the discussions in the most advanced technology developments. They are important for medical applications, but in general, external to the context of manufacturing systems. The current development trends are coming back to original purposes closely associated with supporting data-driven decision-making in realistic time for continuous dynamic processes with very strong safety constraints. These models were usually defined as "virtual sensors", enabling indirect measurements of physical quantities.

This evolution of the concepts is following the orientation of the recent developments of dynamic predictive Collaborative Digital Smart Enterprise, associated with advanced technologies such as Cyber-Physical Systems, Internet of Things, and Industry 5.0. Cyber-physical systems allow real-time enhanced modeling of CPS behavior, decision-making, and control-oriented integration of all the physical and digital components of the system with very capital-intensive components. The IoT Infrastructure provides data collection from entities with embedded sensors and actuators and also analytical and information systems for conducting knowledge and decision-oriented advanced analysis of Data.

2.3. Applications in Manufacturing

Digital twins (DTs) are a pragmatic instrumentation and process data post-processing approach, connecting the physical world of manufacturing, supply chain, logistics, and product design with the virtual computational emulation tools of Classic Mechanical Engineering, Mechanical & Civil Engineering Physics, and Computer Science based modeling, simulation and optimization. The data-driven twin offers rapid deployment and shorter development times than the traditional physics-based twin combination. The fact that the digital twin is built from the primary operational data from sensors, controllers, machines, and devices makes it transportable across similar functions inside and outside the organization without the formidable challenges of transferring a proprietary physics-based twin from the developer to the user. In addition, the use of the digital approach helps build, train, and deploy generative AI versions of the physics-based models and algorithms that are now the focus of attention. Apparel and shoes were among the first sectors to adopt digital twin technology. For example, the automobile maker has DTs for its manufacturing facilities, with applications including discovering how to smoothly schedule production, where to better site logistics support, and managing the interconnected resource constraints. We highlight three core areas of DTs in advanced manufacturing systems: a design area dealing with the DT functions embedded in design specification; an operational area that uses digital twins to guide scheduling and operations; and an optimization area solving the twin challenges of generating the actual schedules and operating the process on the factory floor.

3. The Paint Manufacturing Process

The present chapter describes the industrial paint manufacturing process, and its sequential flow from receipt of paint raw materials to the final product, and its delivery to customers. Furthermore, the chapter identifies the main stages of manufacturing and discusses the quality control operations found in the production flow. Knowledge of how the actual manufacturing operations from which the production data is collected and stored in systems offers a deeper understanding of the relationship between the paint operation's variables and the outcome models. Paint products are used in protective coatings and decorative treatments of buildings, vehicles, containers, and various other consumer products. Coatings play a key role in preserving the assets to which they are applied, by safeguarding them against corrosion, UV rays, chemical agents, and other actions of nature, as well as providing design enhancement properties.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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Industrial paint manufacturing is typically carried out in large vertical agitated tanks or vessels. Its production flow involves several subprocesses. It begins with the receipt of raw materials that are supplied to the production process, in bulk or packed and delivered in trucks or pallets, and the qualification and selection for the paint to be produced. The qualified raw materials are then transferred to staging areas, and the paint, in bulk or packed, is sampled for quality control, certified, and delivered to customers or sent to warehouses. The paint manufacturing process is divided into two general parts: the paint production and the paint quality control. The actual production of paint, which may begin with the addition of the aqueous phase or the solid pigments to the main vessel, consists of milling the batch in the presence of glass beads, followed by stirring for homogenization and degassing. The machine helps to eliminate any entrained air bubbles from the paint that might cause defects during drying.

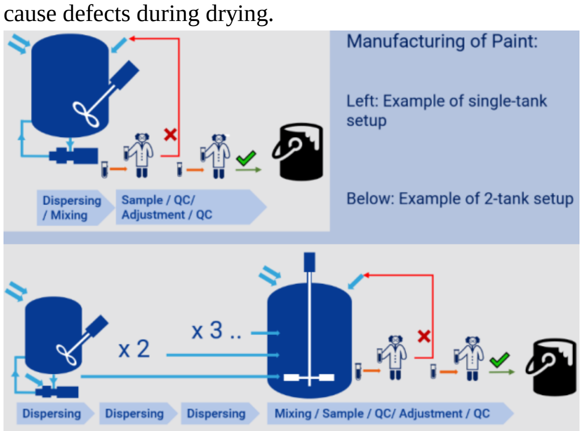

Fig 2 : Manufacturing of Paint

3.1. Overview of Paint Production

Coating systems are composed of different kinds of dispersed and polymer solutions. The term paint designates a wide range of products used to coat, protect, or decorate surfaces. Nearly all manufactured articles are coated and thousands of paint formulations exist to serve their specific purpose. Although it is regarded as a surface finish product, more than 80% of the total paint consumption by weight constitutes non-dry paint, paint on the production line, while dry paint is not used for surface protection and decoration. Non-dry paint, accordingly, is subjected to quality assurance measures that assess the applicability of severe conditions that the coating film that will be exposed. Tests to evaluate scratch, blush, corrosion, chemical resistance, and right drying time are a few of the long list of quality control tests that coating systems have to comply with.

The main function of paint is to form an adherent, continuous, and uniform film on the surface of the workpiece protected by this film. This film provides the surface with good protection from corrosion resistance and electrical insulation; good reflection of visible and infrared rays, good weather resistance and durability; good mechanical and hardness resistance; good adhesion and cohesion resistance; good glossiness and decoration color; and low toxicity or no toxicity after film formation. Film formation is an essential step of the coating process, where the drying of the dispersed phase occurs. The dispersed phase is composed of polymeric particles capable of forming a polymeric network that fulfills the above-stated normal conditions of a coating system after film formation. To fulfill all requirements imposed by the market, different additives are incorporated into the film to achieve specialized coatings.

3.2. Key Stages in Manufacturing

As conceptualized previously, content describes how data supports processing progression. However, this section elaborates on how information on paint product design and chemical ingredients influence the generation of a paint product according to design specifications. This section delineates the principal tasks involved in paint production to aid analysis of how data processing decisions intricately alter how high-quality paint products are generated from a complex set of raw materials. Painting, in laypersons' understanding, is the application of a coat of a given color, typically consisting of pigments dispersed in a liquid vehicle on a surface. The resulting film, once dried, protects the substrate from the effects of the environment and provides a specific appearance. Paints are applied to surfaces in either liquid or powder form—liquid mainly by brushing, rolling, or spraying; powder through an electrostatic process; and curing at elevated temperatures.

Manufacturers supply the raw ingredients to be mixed according to the formula conversion factors for the products. The mixing stage follows a recipe for the desired finished product configured to meet customer specifications. The mixing phase incorporates colorants, extenders, resins, additives, and solvents into a slurry. The slurry, is then sent to the ground for dispersion in a closed vessel fitted with a high-speed disperser and thick film applicator. The slurry is distributed on top of a coating substrate, which passes with the applicator across the machine at a specified speed and then moves to an air-drying zone. Depending upon the product, the slurry is usually from 20% to 80% pigments. Following dispersion, quality control samples are drawn, and assessments are made to ascertain density, viscosity, grind, and opacity. Mixing results are passed to the computer system's process monitoring file and logged for computer analysis reporting general process health complaints back to the user.

3.3. Quality Control Measures

To ensure that the final products feature the expected properties and characteristics, different tests are performed

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during various stages of production. We can define three types of quality control measures:

• Incoming goods control: aimed at checking the validity of the specifications of the raw material before being set into production, the tests performed during such phase are mainly related to physical properties of the incoming goods, the chemical reactivity, and the hazard analysis.

• In-process controls: aimed at ensuring that intermediate products formulated during the batch production lead to almost the same characteristics of those of the previous validated batches, the control tests are mainly the colorimetric measurement, viscosity analysis, and pH measurement of the formulation.

• Final inspection tests: aimed at validating the characteristics of the final products, the measurement techniques depend on the product's destined use and can involve different properties like gloss measurements, haze determination, pigment volume concentration calculations, and/or other unfinished characteristics considered essential.

Thanks to the large support given by measurement devices, quality testing is today much more efficient than before. Examples of highlights in this direction can be given concerning the colorimetric measurement, once performed using colorimetry boxes and visual factors. Today, the emerged illumination and the color difference evaluation are made by devices that have been designed to be able to emulate the response with filters characteristic of the observation of the human eye.

4. Data Engineering Fundamentals

Digital Twins are a well-known digital representation of a physical object or object, which at desired frequencies, can be synchronized against actual, real-world, measurements in a closed-loop manner. An Industrial Digital Twin represents such a representation of a machine, factory, or entire company. To implement e.g. a Machine Digital Twin it is mandatory to have a model and to have the sensor data as input, that is synchronized against the model predictions. Implementing these two inputs is called data engineering. The term Data Engineering describes the field of IT that deals with processes and systems for the collection, storage, integration, and distribution of data, irrespective of whether it originates from sensors, RPA, events from other applications, or external partners.

Data Engineering is an essential part of Artificial Intelligence and other data-driven Systems. Data Engineering ensures that such systems have high-quality datasets available for analysis. The term Data Engineering doesn't explicitly tell one how to implement the systems but rather describes the characteristics of such systems. In a Machine Learning context, Data Engineering tools and libraries are e.g. TensorFlowData Validation, Apache Beam, or DBT. Data Integration or ETL is a subfield of Data Engineering with a major focus on the data pipeline activities of integration and storage. Data Pipelines create the data by integrating, cleaning, and preparing the data. Data Pipelines are essential for any data consumer, be it Business Intelligence, Machine Learning, or Random Process Automation. Be it a prediction or actuation, a consumer needs the right data at an appropriate time.

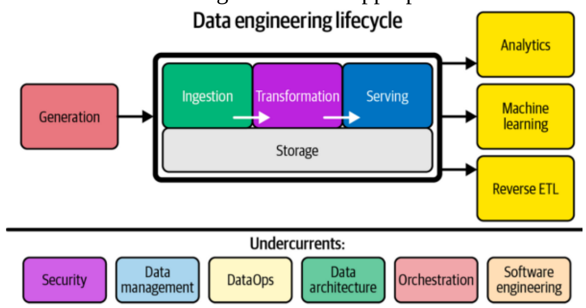

Fig 3 : Fundamental of Data Engineering

4.1. Data Collection Techniques

Data collection is a process in which a system gathers and measures information from different sources that is added to its data model or updated in the operational data repository. Data collection could also be understood as the process of turning physical phenomena into bytes. The implementation of this process can be tricky because it involves dealing with various engineering challenges related to sensors and measurement techniques. In this chapter, we introduce key aspects related to data collection that are important for building operational data repositories.

In a digital twin system, outbound data is gathered from the physical system to create and update the digital twin data model and the operational data repository. The digital twin's operational data repository holds a time-indexed collection of variable values that represent the behavior of the physical entity tracked by the digital twin during its activity. Data available from the physical system is collected in real time and is used to update the digital twin. Such data is often reported by sensors that measure certain physical phenomena and is normally transmitted to a computer or cloud server for storage and processing. In other applications, time-indexed data is available only at certain times or events from the physical twin and may be collected by humans or machines. Such data is generated from an abundance of data sources relating to the physical entity, its digital counterpart, and the environment around them, but at the same time, those include high variety, high volume, and high-velocity data that often is heterogeneous.

4.2. Data Integration Strategies

Data collections are often heterogeneous; different sensors generate data with different temporal, spatial, or semantic patterns. Using a wide range of state-of-the-art smart

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sensors, such as RGB and hyperspectral cameras, laser-induced breakdown spectroscopy, health sensors, and so forth, we collect data for cyanoacrylate-based paint production. Color matching builds the basis for successful product acceptance. We have multiple RGB image collections with varying parameters, such as illumination position, environmental lighting, or RGB color tube combinations, in addition to HS images. The former has been made using the grating technique, and the required time for the manual preparation is 3.5 sub-session days.

Paint has been applied to substrates similar to those on which color matching is performed. Periods during the application of paint to the substrates correspond to data collections related to the points of interest for RGB and HS image-based color matching. Therefore, data from these two sensors in addition to temperature, pH, and viscosity data, would be highly relevant for quality assessment of the substrate color matching. pH and viscosity data corresponding to the interesting points of RGB and HS images are stored in the same database as these pigment- and dry paint-related images. The temporal data collection synchronization for the HS image color-matching quality assessment is more costly regarding the required resources than for the RGB technique. For these reasons, HS image data collection occurs less frequently than that for RGB images.

Understanding the reasons why RGB and HS images could not match color-wise, thereby leading to the usage of other shades for on-substrate pigments, would help color affordable matching, in addition to saving time and costs related to pigmenting and production of the entire batch using the discovered mismatching pigments. The final developed pigment mixture color is calculated using a model. This model can be used in addition to other models. RGB and HS sensor fusion color estimation of dry paint and the association between substrate paint color quality and temperature, pH, and viscosity parameters at those reference timestamps of pigmenting is made easier given the corresponding RGB and HS color-matching pixels.

4.3. Data Storage Solutions

In the context of Data Science, a prominent key aspect is Data Storage, namely securing reliable – and optimally long-term and efficient – access to the various Data Sources. The existing tools and technologies covering this fundamental area have burgeoned over the last decades, thus rapidly accommodating organizations and companies in addressing their Data Storage needs. However, the ever-growing Data Lakes imposed by Data-Driven approaches also leveraged unprecedented Data Storage challenges – both in terms of requested resources and complexity for seamless querying – that require innovative and cutting-edge solutions. Data Storage is considered an integral part of the Information Management Ecosystem, together with Data Governance and Data Integration. In this ecosystem, the convenient role of Data Storage Solutions is to construct the proper infrastructure to perform the operations managed by Data Governance Policies, focusing on the Data Integration management plan functions. However, many organizations and companies often devote less attention to Data Storage Simplicity and Efficiency than to Data Analytics and Data Management layers, which risk incurring severe ramifications. Typical examples include the excess number of copies stored in Data Lakes or the trading off for speed versus compliance. Unfortunately, these issues are commonly discovered in the Life Cycle of Data Products, often leading to bottlenecks or increasing infrastructural costs.

5. Digital Twin Frameworks

Given the broad range of applications that Digital Twins offer, a diverse set of framework implementations have been presented, particularly for specific industries or technologies. We classify them into three categories: architectural models, simulation techniques, and real-time data processing. Frameworks may also belong to multiple categories; for instance, to study the system dynamics of a two-level manufacturing architecture, a digital twin using agent-based modeling has been proposed and demonstrated with a system dynamics case study. The study utilized a digital twin for discrete-event simulation and system dynamics, illustrating the power of combining different methodologies to help guide real-time decision-making with feedback from the physical system.

While some architectural models are described clearly and specifically outlined, it is not uncommon for architectural models to not go into the specifics of the twin's implementation. An architecture is defined by four elements: the abstract model, the smart object, the interoperable infrastructure, and the application interface defined by smart manufacturing processes. The abstract model represents the digital object and relates to its physical counterpart; the smart object is the digital object itself; the interoperable index serves as a link between the smart object and the abstract model; and the human-machine interface interacts with the user's needs. Consistent with this study, the presented architecture takes components of smart industry and cyber-physical systems. The digital twin focuses on information management, requiring the use of a model-driven methodology with a feedback service layer for dynamic systems. The layers provide adjacent systems with the architectural levels of abstraction necessary for real-time simulation and data storage in the twin. In their framework, the models used for the twin are intertwined with the layered architecture, particularly focusing on aspects of the modeling methodologies utilized in the twin development.

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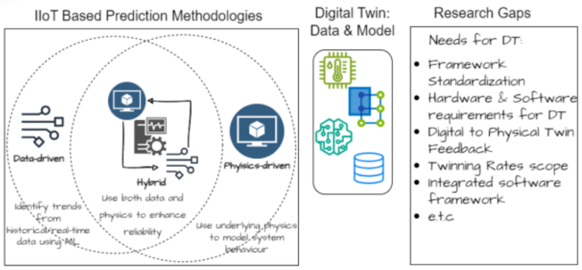

Fig 4 : Digital Twin Framework for Predictive Maintenance

5.1. Architectural Models

Digital twin frameworks, as represented by architectural models comprising large, interdisciplinary layers of applications and simulations built on specific digital technologies, provide an enabling design for diverse digital twin systems in many domains. Such frameworks drive the concept of digital twins in practice and provide the basis to implement principles and concepts, such as data hierarchy, semantic rules, interoperability, and other factors. In parallel, application domains as well as specific demands, such as security and safety, adapt these generic frameworks. This results in specific architectural extensions, such as semantic ontologies, for instance, extended to specific phases within the product/service life-cycle.

Domain-specific digital twin systems adopt and adapt cross-domain architectures and frameworks. Various bodies define frameworks for industrial sectors from simple, three-layered solutions to complex, model-based life-cycle support and data flow architectures. Architectural big pictures present layers with major groups: data services, model services, simulation, and physics engine, data and simulation orchestration, and functional service for robot-based and AI-enhanced intelligent support. Computer-integrated manufacturing domain solutions introduce layers of service-oriented architecture with layers representing resource service encapsulation, orchestrating services, implementation of resource service, and a top layer for conducting business logic. Smart factory innovations define smart factory architectures conceptualizing dedication finance-drive implementation types of smart factories.

5.2. Simulation Techniques

In this chapter, we discuss how digital twins differ from digital models and what simulation techniques are supported in digital twins. We focus exclusively on techniques where the one governing the real system is involved and thereby present "closed loop" (or "feedback" or "interactive") simulations of the real system integrated into the digital twin that can run in update time or real-time or that run significantly faster than real-time and, therefore, demand asynchronous and discrete access to the real system to allow at least some timing under-constrain conditions. These techniques, however, are not all "predictive" and "what-if analysis" in the same sense. For ephemerally non-predictive techniques, that is, techniques that are predictive only for short periods, feedback control is an indispensable permanent component. This chapter also provides an overview of what we call "non-Digital Twin Model Usage," for example, what we call "heuristic," "manual," "real-time tuned," or "remote DSP—Drift Space Physics" approaches. Digital twins differ from the schemes outlined in this section by way of their strict formalization.

We summarize techniques that are not strictly digital twins in the following, including physics-based but asynchronous methods for real-time tuning "non-digital twin models, emphasizing their advantages and applicable use cases. The techniques summarized in the following rely on decreasing levels of formalization, meaning that in a large majority of cases, they are not realized in the form of software programs. There exists dramatic asymmetry regarding the real-time applicability of either technique. The physics-based, deterministic methods have, until recently, not been suitable for real-time applications. The models are based on long-term observations of the progress of physical or natural processes, results from simulations, or physical and natural laws.

Equation 2 : Multi-Objective Optimization Function

$$J = \alpha \cdot Q - \beta \cdot E - \gamma \cdot T$$

Where

J: Optimization Objective

Q: Product Quality Score

E: Energy Consumption

T: Processing Time

α, β, γ: Tunable Priority Weights

5.3. Real-time Data Processing

A digital twin requires continuous updates and modal synchronization to reflect the assets that it represents, which is one of its characteristics that differentiates it from a traditional simulation. What differentiates real-time digital twins from other digital twins even more is the speed of data update and the velocity of the operation being modeled. While the digital twin may communicate close approximations of the real system behavior, it might not necessarily need to reflect the same system results in exact time. Real-time digital twins employ a stream data approach type, which is a computational model capable of ingesting, storing, processing, and analyzing massive quantities of data in real-time with low latency.

Stream data processing has become essential in advanced technological areas related to the concept of Industry 4.0.

Due to its importance and the massive investment in this area, a plethora of tools, algorithms, frameworks, and models have been developed to tackle particular problems in which stream data processing occurs. All these items can be categorized into the following groups of building blocks for stream data processing systems: data collection, stream data storage, data enrichment, data processing, and data sharing and distribution. A digital twin may rely heavily on existing cloud computing services to support the infrastructure to tackle these building blocks – for example, using mass storage alternatives combined with a managed database service or a managed streaming data service that supports near real-time distributed processing. Alternatively, it may rely on dedicated local edge solutions, using open-source tools.

6. Process Optimization Techniques

The development of digital twins for paint manufacturing factories enables a whole range of applications. The digital twin not only serves as a visualizing tool but also assists production managers and engineers in improving production planning and becoming aware of possible problems in the production process. The digital twin can forecast production events for any time of the day or week. This capability can assist in scheduling production during less hectic times of the week or day. A heat map of abnormal conditions that is based on historical data can be used to develop production timelines that ensure a more efficient production process. Predictive analytics can predict a range of output variables. For example, quality metrics like the gloss level or cracked paint surface can be predicted, but so can productivity metrics like throughput or batches that exceed the time limit. While typical predictive equations rely on physical relationships, plant data as gathered by the digital twins, and machine learning techniques allow the development of more sophisticated models. Supervised learning algorithms can be learned that can discover correlations between input variables and the plant output. They can identify conditions for low throughput or low quality. Statistical quality control can be updated with more timely data. Self-tuning controllers can call input conditions that would restore operating at the center of the prediction envelopes. The availability of vast amounts of plant data and the more recent development of powerful machine-learning methods promise to accelerate this field.

6.1. Predictive Analytics

The growing amount of data generated in production processes gives businesses new and significant opportunities to improve their manufacturing processes. Data-driven technologies utilizing dispersed data enable fast product development cycles, improved process reliability, and lower production costs. While principle engineering, knowledge engineering, and data engineering approaches can be applied to manufacturing processes, the data engineering approach provides many opportunities to gain more insight and prediction capabilities from large amounts of data currently stored.

In predictive analytics, empirical statistical models and machine learning are used to improve knowledge from data, and the insights derived can be employed in operator decision-making or automated online closed-loop process control. A range of operator decisions can be enhanced using predictive analytics including corrective action, parameter adjustment, or new batch recommendations. In closed-loop production decision automation, the predictions can be embedded into safety control systems that can automatically adjust production parameters, or into dynamic process management solutions that intervene based on advanced failure predictions. Another exciting option is to connect insights from predictive analytics with enterprise-level business process decisions and activity planning in enterprise resource planning systems. Although the latter presents challenges in terms of process decoupling and response time, there are many opportunities to optimize operational production cost-effectively.

6.2. Machine Learning Applications

Machine learning in process control has been widely applied in a variety of industries with remarkable success. In the domains of oil and gas, aerospace, energy, and transportation, tasks such as fault detection, anomaly recognition, and predictive maintenance have benefitted significantly from the implementation of neural networks, random forests, and decision trees. Similarly, industries such as agriculture and manufacturing have also seen similar pros in terms of costs and interoperability. In the chemical manufacturing processes specifically, myriad machine learning applications exist. Drinkable water is one of the most sought-after resources on our planet. The purifying process of chemical parameters plays an important role in ensuring drinkable water. Several chemical parameters such as turbidity, pH value, temperature, oxidation-reduction potential, total dissolved solids, conductivity, etc. have been monitored using the design of experiments. These parameters help with the optimization of water treatment. However, these parameters have been found to have a high level of non-linear correlation. Thus, a machine learning-based method would provide better results compared to the traditional linear regression method.

Other than water treatments, several chemical industries, such as dyeing and chemical etching, have also incorporated advanced machine-learning methods for color predictions. It has been found that the multivariate analysis method can predict the color of a dyeing process using the monoparameter analysis and then the evaluation of dyeing performance by K/S value. Nevertheless, although the application of machine learning in real-world paint production has seen little success, there is a research study that discusses this gap and proposes a machine learning method using a hierarchy of RGB and YCbCr color space using deep learning for color predictions of paint mixtures.

6.3. Feedback Loops in Production

To conclude this section, the modern manufacturing industry has an increasing need for platform systems and services that combine real-time production data and industry building blocks. Moreover, the industry is in a state of transformation where automation and automatic processing have surpassed predictive maintenance processes. Even if the latter remains useful, we are continuously witnessing the advent of industrial systems and services that have opted for an iterative data loop and feedback loops in production. DDC systems hosting DDP live for the goal of automatic monitoring and control of production parameters. These systems command and control the production process by iteratively configuring its operating parameters. The two loops in charge of configuring the operating parameters of the production process are data analysis feedback loops and kinetic production loops.

The data analysis feedback loop analyzes the data generated by the capital-based systems governing the production process. Why do feedback loops in production such as DDC systems hosting DDP live and command and control the data kinetic loop of production rather than the data kinetic loop of production? The data kinetic loop in charge of streaming and roll-up data enables a two-fold data processing chain. The first chain contains variable data velocity for a considerable portion of the data. This chain cleans the raw data with clearly dominated noise components. Then, the data is archived and transformed thanks to a low velocity of the subsequent data roll-up operations. The first leg of the processing chain is data energization and the second is data enrichment or data boosting. The ensuing energetic and boosted data will be then used in the voltage feedback leg of the power kinetic loop to decrease lost production hours, while the boosted data will be used in the data analysis feedback leg of the DDC data loops to increase production efficiency during the production operating time.

7. Case Studies

Empirical observation is paramount and should be prioritized when constructing a digital twin. The importance of practical case studies when developing data engineering tools is not only that they show the methodology in action, and how it can be useful, but that they illuminate poorly understood and unexplored corners of complex realization. Here we present the study of several case studies where client companies have successfully achieved significant gains by using current digital twin technologies. Digital twins are not yet commonplace in the paint manufacturing domain, and this paper aims to multiply such successful stories in the future.

These realization cases are not a panacea. Some of our experiences have met with skepticism. For example, the near real-time data notification can be perceived as a security breach, which creates uneasiness in some operators. This results in retrospective denial of some plant episodes reported by the data systems. Another case is a plant where spray paint defect detection, used recently to enhance the twin sensor, provides false replies. That reduces data usage acceptance. However, our experience points to another barrier: the inability of domain experts to find a significant advantage for the digital twin. While this may be a showstopper for some implementations, for other projects the lessons learned seem to point to the importance of a user-centered design approach. Domain experts in a mentoring role provide the basis for developing secure and useful systems and applications operating software. Practical implementation and occupation depicting how data systems act turn skeptical experts into advocates, providing the best defense against future disadvantageous risks of data occupation in the paint shop.

7.1. Successful Implementations

In this chapter, we show three digital twin implementations at different levels of complexity in paint manufacturing. In these implementations, we find trade-offs between the impact that we expect to have on process optimization and the complexity of the modeling, data, and software engineering needed to successfully and sustainably deploy the digital twins. These trade-offs motivate our final recommendations about how to build different generations of digital twins that address the increasing complexity and added value of novel Industry 4.0 solutions and services.

Our first implementation is a simple mostly static dashboard based on prescriptive analytics that shows production and laboratory data for a thickener usage that is optimal from an acid number perspective for the wanted viscometric profile if this acid number is given as an input. It is simple because at the technological level is only a dashboard of mostly historical data. This implementation allows for comparison with historical data in the laboratory, which should have a differentiation concerning the others to be useful in the analysis. This tool has proven useful for understanding thickener performance concerning production variability and making conscious decisions when interrelations with production are identified. A future version of this digital twin could update the suggestions on the optimal thickener dosage to tune the paint viscometric profile dynamically

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when an acid number is given to maximize the performance of the thickening agents identified to be sensitive to production variations. This next stage would require a small amount of data engineering and statistical knowledge to decide when model recalibration is necessary.

7.2. Challenges Faced

In painting manufacturing, there are numerous challenges when leveraging Digital Twin. Depending on the use case, the technological challenges affect the need for the virtual model to work in real-time and the complexity of the process chain required. In some cases, it is nearly impossible to model the chemistry reaction at the molecular level within real-time constraints. This is an even bigger challenge if the Digital Twin has to run off the cloud, which is often the case in real use cases. In other applications, the challenge does not lie in the real-time need for complexity but rather in the vast quantity of available data that must be brought into a coherent data model and virtual model. For these cases, the challenge is the ease of data ingestion and data mining based on domain knowledge, and on the other hand also the efficiency of visualizing results in an intuitive way for the user.

The organizational level challenges can be due to an unconvincing value for the user or a perceived lack of integrability. Often the decision to build a Digital Twin is top-down rather than bottom-up for the specific use case. However, it is usually a requirement from use cases to have the user purpose-driven involved in creating the Digital Twin model. There can be problems perceived in a lack of integrability. While the Digital Twin model first needs to be built, this should be an ongoing process that does not require an overhaul under changing use cases. Particularly at the shopfloor level, the use cases may change over time. However, the people who are the experts who can easily modify the model may not be there over time. This comes into play when the experts want to embed their domain knowledge but are simply not there at the later stage of using and updating the Digital Twin regularly.

7.3. Lessons Learned

The end-user is looking for a usable solution instead of a fancy one. Improvements in data engineering pipelines should be visible in business results, such as shorter delivery times and less rework. Digital twins act vertically and horizontally in all value-added services: development and customer assistance, input, and process optimization. Technologies are maturing, costs are decreasing, and supply chains are more and more exposed to uncertainties and variability. This creates the perfect environment for a "why not?" with engineering teams requesting experimental prototypes to be used and validated by process leaders. However, data engineering cannot be treated as a one-off project. The more data engineering-as-a-product is structured, the more returns on investment will be obtained. Technology becomes an obstacle only when not properly designed and correctly installed. Data engineering as a product becomes vital in this case. The digital twin becomes an environment where chemists or engineers can explore multi-dimensional representations of the effects of the input control on the output response while also accounting for the production process. In this phase, they would only be aware of the presence of the digital twin and would ask for it to run simulations for their tests whenever there is a need, openly defining both the models used in the exploration and the test conditions. This reverts the roles of data engineering and data users. The best practice aims to free the data user from the constraints of data engineering design choices, estimated test conditions, and test execution to bolster creativity while ensuring safety.

8. Future Trends in Digital Twins

Digital twins have evolved as one of the most prominent monocles into the upcoming next-generation digitalization concept. Whereas its original inception took a singular and yet very grounded viewpoint, the growth of associated enabling technologies, such as Blockchain, AR/VR, AI/ML, Cloud, or Edge Computing is introducing additional opportunities of a much more sophisticated nature. To some degree, digital twins can also allow a personalized digital representation of the respective spaces of interest. In this way, High-Level Digital Twins can also become potentially part of the Industry Metaverse, as the combination of industrial processes and spaces; immersive interaction experiences; and purposeful virtual experiences create benefits for the physical world.

It is also a fact that digital twins are and will be continually integrated with other Industry 4.0 technologies in a non-democratic way. Digital twins are connectors or enablers of different Industry 4.0 technologies. This statement is a direct consequence of the intrinsic and explicit definition of digital twins. Increasingly being an enabled technology for dozens of applications in dozens of business sectors, including applications as self-healing processes, predictive cybersecurity, individual optimization of resource utilization, closed-loop virtual design testing, decentralized collaboration under security, or sustainable design, digital twins will create immeasurable amounts of data. These data will be at the service of all the stakeholders involved in every social, economic, or environmental dimension of every business application.

Finally, the three sustainability dimensions are the ultimate objective of all Industry 4.0 digitalization technologies, which reduce costs, increase profits, and at the same time create valuable, durable, and responsible products, services, and solutions for customers. Thus, by optimizing existing processes or business practices throughout each of their main stages, digital twins become a key enabler in the World's roadmap to multilateral sustainable development.

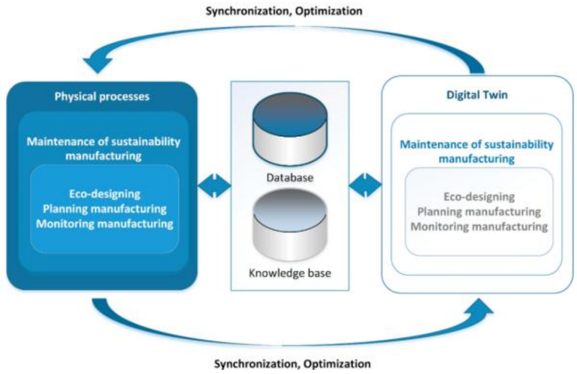

Fig 5 : Digital Twins in Product Lifecycle for Sustainability in Manufacturing and Maintenance

8.1. Emerging Technologies

As digital twin implementations become increasingly widespread, several other technologies will intersect and overlap with digital twins to strengthen and augment the user experience. We refer to these technologies as underlying technologies. These underlying technologies include AI and machine learning, Edge computing, the Internet of Things, Blockchain, Augmented and Virtual Reality, and 5G networks.

AI and machine learning democratize predictive and prescriptive analysis for non-data science experts. More advanced machine learning pipelines exist today than ever before, with products and platforms available. Although deep understanding and proper error checking of the results from AI/ML technology still require data science experts, the technology is improving quickly. It is connecting with digital twins through the software-as-a-service approach and utilizing lower-fidelity twin versions to find reductions of thousands of possible variables in complex business and production simulations.

Edge computing provides lower levels of latency and greater levels of processing than relying purely on the cloud. Devices close to data acquisition generation points and also close to actuators and automation gear for the virtual twin can have onboard digital twin models to analyze purpose-specific data at higher speeds. They can communicate their results and actions with higher-level cloud-based digital twins. Digital twins can become much faster and more autonomous thanks to collaboration with their edge devices, especially for fine-timing systems in critical levels of operations. As both edge-computing technology and cloud computing architecture improve, the collaboration between digital twins and their edge-device partners becomes more important than ever.

8.2. Industry 4.0 Integration

Digital Twins are currently associated with Industry 4.0 through continuous data streams, which enable an important step towards Data-Driven Manufacturing Automation and Self-Optimized Processes. The Industry 4.0 concept proposes three important pillars in which there is a synergy: Cyber-Physical Systems, the Internet of Things, and Big Data. Cyber-physical systems are defined as systems in which the physical and computational elements are deeply intertwined, and there is a feedback loop and a continuous two-way interaction between the physical and computational elements. In the industry sector, Cyber-Physical Systems refer to automated systems of the factory. These systems have been incorporating more sensors to increase and improve the data collection from the process. One particular evolution of Cyber-Physical Systems is the Digital Twin, which refers to the combination of a physical entity and its corresponding virtual entity that has the function of monitoring, simulation, and optimization of the physical twin through the use of data. The Cyber-Physical Systems are the core of the Industry 4.0 concept; indeed, there is a strong influence between the two concepts where Cyber-Physical Systems serve as an enabler for Industry 4.0, and the Digital Twin concept is built on the Cyber-Physical Systems and it is called the next generation of Cyber-Physical Systems.

In a factory, there are several pieces of equipment with the incorporated technology of IoT. This technology consists of a unique identification of every device connected over a network where information and data can be exchanged and collected at any time. This connection of the devices allows the constant flow of Big Data which are crucial for practical applications of the Digital Twin or Digital Thread. The Digital Thread concept refers to the communication framework that allows a connected data environment to exist, providing an integrated view of asset data throughout the asset's life cycle across different functional disciplines, leveraging data that is both structured and unstructured. The Digital Thread connects the data flows across the different manufacturing stages enabling continuous optimization of the lifecycle of the systems and processes both at the design and operational phases.

8.3. Sustainability Considerations

Humankind is facing a series of unprecedented challenges that threaten social and environmental stability: climate change is expanding rapidly and coming to be understood as the absolute priority for defining the relations between human societies and our planet. To prevent the most catastrophic scenarios, industrial emissions must be reduced to achieve carbon neutrality by mid-century; a complex agreement given that emissions must peak before. Paints and coatings are present in virtually every aspect of the built

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 34 Issue 2, July-Dec 2024, Pages: 1202-1218

environment and they are responsible for a not insignificant portion of global emissions of VOCs. Furthermore, coating processes also consume a bulky amount of energy, and all systems and subsystems involved in them ought to be optimized to the fullest. However, digital twins are machine-learning enabled, which means that aside from preserving mathematical information that relates the present with the past, they are also useful for understanding behavior through correlations and forecasting, which is something quite unusual for a machine-learning algorithm. This is possible thanks to the fact that digital twins add a layer where mathematical rules are introduced. Such rules have been proven useful to refine the prediction of any machine-learning algorithm, in several use cases.

Thanks to their accuracy and interpretability, digital twins become invaluable tools for the optimization of processes toward sustainability goals. Moreover, they are in place at the core of a digitalization action inside the Industry 4.0 framework, which drives traditional businesses, like paint manufacturing, toward almost complete automation. The fundamental principle is that digital operations are more efficient, errorless, safer, and responsible from the point of view of the sustainability of human capital since they are not subject to traditional, tiresome, and unsafe operations that human laborers need to perform. Digital twins of backend operations are helpful as core technologies for data-centric constructions, which make heavy usage of building information modeling processes driven by finite element methods.

Equation 3 : Data Fusion Score for Twin Accuracy

$$S_f = \frac{1}{n}\sum_{i=1}^{n} w_i \cdot \mathrm{Corr}(X_i^{sensor}, X_i^{model})$$

Where

S_f: Data Fusion Score

X_i^{sensor}: Sensor Data Stream

X_i^{model}: Simulated Data Stream from Digital Twin

$\mathrm{Corr}(\cdot)$: Correlation Between Paired Streams

w_i: Importance Weight of Each Feature

9. Conclusion

In conclusion, the work has presented different data engineering approaches based on digital twins to reach theoretical hypotheses within the manufacturing of paint-related products. These approaches allow the industry to optimize processes, through a precriteria and the implementation of data-driven actionable insights. The proposed agnostic digital twin requires minimum effort for implementation and can be performed by industry personnel. In particular, low input values of the amount of data needed for credible predictive models while analyzing the effects of data distribution with a physics-driven approach, along with intelligent data filtering, have a direct impact on closing more use cases from existing process historical data and industrial-informed hypotheses. The results make data-driven approaches more appealing and feasible to implement in paint manufacturing industries. Future work will focus on expanding the number of digital twins to cover a wider scope of manufacturing processes, such as glaze manufacturing for ceramic applications and the coating of steel. A second future direction is to implement anomaly detection to be integrated into paint manufacturing industry decision management systems in real-time to prevent errors that affect product quality and manufacturing costs. A third line will center around the deployment of decision management systems based on data-driven and physics-informed twins that help industry experts reason and discover relationships between noise sources in paint manufacturing and product qualities that require constant monitoring during manufacturing. A last research direction is the automation of data engineering activities identified in this work, such as data cleaning, data labeling, engineering, and model training, to increase the number of processes where data-driven and physics-driven digital twins are proposed, which require less supervision and a more expert-driven approach to the implementation of digital twins.

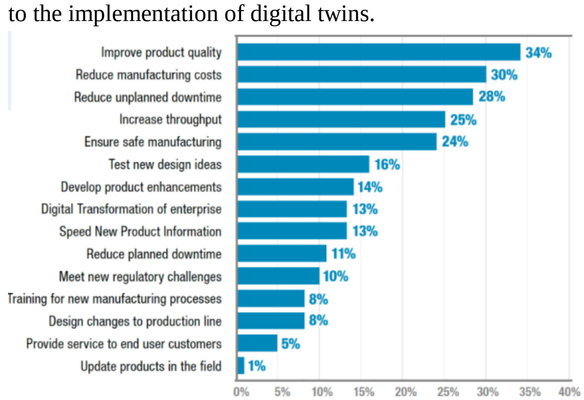

Fig 6 : Digital Twin Technology

9.1. Key Takeaways and Future Directions

In this work, we analyzed the new challenges for paint manufacturing brought about by the Fourth Industrial Revolution and the Digital Twin concept, presenting a specific focus on data engineering approaches for the construction and deployment of Digital Twins that can be applied to paint manufacturing processes. We outlined why Data Engineering for Data Ingestion, Filtering, Contextualization, Storage, and Data Inference is a key task in the Digital Twin life cycle, with connections and impacts across all the other tasks: Data Connection, Synchronization, and Management, Digital Twin Modeling and Simulation, and Digital Twin Action and Operation. To exemplify how these data engineering tasks can be applied, we presented what we called a Paint Data Engineering Framework, which can be assembled from four key Data Engineering patterns: the Layered Data Architecture, the Data-Driven Digital Twin Model, the Context-Driven Data Synchronization, and the Data-Driven Action and Operation Patterns. Lastly, we reinforced and discussed these ideas through three use cases, exposing Digital Twin candidates that can be explored in the paint manufacturing industry. Going further, we must highlight some of the key aspects that we believe are important for future research in this area. First, even though one of the main outcomes of the Fourth Industrial Revolution was the availability of low-cost sensors for collecting data that previously were regarded as impossible to obtain, the design of a Digital Twin is usually data-driven. In the Extreme Paint Makeover use case, we relied solely on simulations for a non-representative set of operating conditions to model and simulate the Digital Twin, and we did not characterize it further on a more representative design space. As such, enabling technologies for the Digital Twin design phase, such as Data-Driven Design of Experiments, along with sample-efficient surrogate models, should be further explored. Second, we explained how the models in the Informatic Stage could contemplate the Digital Twin model components and parameters.

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Vol. 34 Issue 2, July-Dec 2024, Pages: 1202-1218

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