ARTICLE IN PRESS
JID: CIRP [m191;June 20, 2023;19:19]
CIRP Annals - Manufacturing Technology 00 (2023) 1–27
Contents lists available at ScienceDirect
CIRP Annals - Manufacturing Technology
journal homepage: https://www.editorialmanager.com/CIRP/default.aspx

# Digital twins for electro-physical, chemical, and photonic processes

Yuebin Guo (1)[a,b,*], Andreas Klink (2)[c], Paulo Bartolo (1)[d], Weihong Grace Guo[b,e]

[a] *Department of Mechanical and Aerospace Engineering, Rutgers University-New Brunswick, Piscataway, NJ 08854, USA*
[b] *New Jersey Advanced Manufacturing Institute, Rutgers University-New Brunswick, Piscataway, NJ 08854, USA*
[c] *Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Campus-Boulevard 30, 52074 Aachen, Germany*
[d] *Singapore Centre for 3D Printing, School of Mechanical and Aerospace Engineering, Nanyang Technological University, 639798, Singapore*
[e] *Department of Industrial and Systems Engineering, Rutgers University-New Brunswick, Piscataway, NJ 08854, USA*

ARTICLE INFO

*Article history:*
Available online xxx

*Keyword:*
Digital twin
Manufacturing process
Industry 4.0

ABSTRACT

Manufacturing processes are becoming increasingly data-driven. Integrating manufacturing data and process models in real-time, a digital twin (DT) may function as an autonomous and dynamic digital replica. This, in turn, may enable manufacturers to not only understand and monitor a process but also proactively control it in real-time or a product over its life cycle. This paper examines the DT concept and its evolution and presents a future DT framework. DTs' key components (e.g., process models) and implementation are focused on additive manufacturing, electrical discharge machining, and electrochemical machining. Furthermore, current challenges and future research directions are summarized.
© 2023 CIRP. Published by Elsevier Ltd. All rights reserved.

## 1. Introduction

Industry 4.0 provides an opportunity to achieve higher levels of productivity through interconnected intelligent elements (e.g., machines, robots, sensors) on the shop floor. The technology allows remote sensing, real-time monitoring, device control, and cyber-physical manufacturing, therefore, enable direct integration and synchronization from the physical to the digital world [142,183]. Digital technologies enable virtual product and process planning through simulation and other various predictive tools for real-time planning. One of these model-based technologies with great potential is Digital Twin (DT) which is the real-time virtual replica of a manufacturing process or a physical asset (e.g., product, tool, machine, factory, people). A manufacturing DT offers the unique opportunity to simulate and optimize the manufacturing system. DT has been explored to increase efficiency, competitiveness, and productivity in different manufacturing areas including production planning and control [204], facility maintenance [48,228], and layout planning [235].

A functionally robust and repeatable DT model should be capable of providing necessary support services such as monitoring, diagnosis, optimization, and control. The current concept of DT spreads across various business and engineering functions, thus blurring its scope and objectives. To facilitate seamless integration of DT, a proper definition of the concept, scope, and framework is a must based on its functionality and goal of bringing in productivity improvements and economic benefits. Amidst the fast-evolving technical landscape, manufacturing systems of yester years will require modification to meet customer requirements and cut-throat competition as the industry continues to integrate and implement smart manufacturing philosophy as part of Industry 4.0. The existing predominant digital and automated workflow in many digital manufacturing processes, such as additive manufacturing (AM), make them ideal candidates for DT. Manufacturing processes involve many process variables (e.g., powder bed fusion (PBF) has more than 150 variables) while translating CAD data to a physical part, these parameters also introduce deviations and part reliability issues [101]. DT can help address the long-lasting issue of uncertainty in manufacturing processes. Considering the growing market of advanced manufacturing, research and development in DT is critical for early technology adopters in the twin arena. Hence, an in-depth analysis of the state-of-the-art technology, current challenges, and a visionary outlook on DT applications in the strategic important manufacturing processes would be very necessary.

According to the Deloitte survey [3], the global market for DT was estimated to grow from US$ 3.8 billion in 2019 to US$ 35.8 billion by 2025, at a compound annual growth rate of 37.8%. The increasing adoption of emerging technologies, such as smart sensing, the Internet of Things (IoT), edge/cloud computing, Artificial Intelligence (AI)/Machine Learning (ML), and Model Predictive Control (MPC) drive the demand for DT. The encouragement from the business potentials of DT in certain industries, e.g., healthcare, aerospace & defense, automotive & transportation, and smart cities, are also prevalent [62]. It is noteworthy that the realization of DT is closely linked with the automation pyramid and cyber-physical systems (CPS) models prevailing in many advanced industrial settings [45].

In this paper, the focus is to provide an in-depth assessment and understanding of the dynamically evolving DT concept, definitions, and perspectives (Chapter 2) of DT technologies. The DT

* Corresponding author.
*E-mail address:* yuebin.guo@rutgers.edu (Y. Guo).

https://doi.org/10.1016/j.cirp.2023.05.007
0007-8506/© 2023 CIRP. Published by Elsevier Ltd. All rights reserved.

Please cite this article as: Y. Guo et al., Digital twins for electro-physical, chemical, and photonic processes, CIRP Annals - Manufacturing Technology (2023), https://doi.org/10.1016/j.cirp.2023.05.007

framework, building blocks, and enabling components (Chapter 3) are proposed to act as the foundation to build next-generation DTs for addressing the gaps in the existing digital workflow. Then, the state-of-the-art of DT and its applications in the energy beam (e.g., photonic) processes (Chapter 4), electro-physical process (e.g., electrical discharge machining/EDM), and chemical process (e.g., electrochemical machining/ECM) are thoroughly analyzed in Chapter 5. The industrial DT trailblazers are introduced in Chapter 6. The thorough analysis also identifies the current technical challenges and outlook (Chapter 7). Last, the key points are summarized (Chapter 8) based on the in-depth analysis.

## 2. Digital twin concept, definitions, and perspectives

### 2.1. Defining the digital twin (DT)

The idea of duplicating physical systems dates back to the 1960s. It was popularized by the famous Apollo 13 mission, where the simulators were physical counterparts to the actual Apollo spacecraft [34] (Fig. 1). There were some digital aspects to them in that they were running primitive computers with the same programs as the actual spacecraft itself. The development of the DT does have a strong connection to NASA. However, the claim that the DT originates in the Apollo program is unfounded. The DT Model idea was first introduced by Grieves in 2002 as a concept for Product Lifecycle Management (PLM), but without a name [71]. The model was later named Digital Twin which is “. . . a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level.” published by Grieves and Vickers [72,74]. While the DT has changed over time since John Vickers of NASA coined the terminology in 2010 [194], the basic concept and model format have remained the same. The first recognition of DT has already appeared in the NASA Technology Roadmaps [183,213].

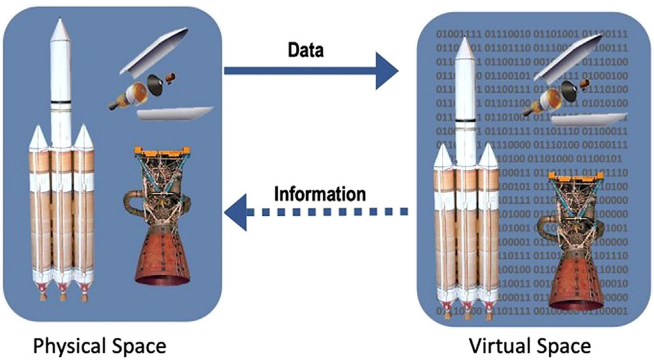


**Fig. 1.** Digital twin concept [72].

While DT in its original concept describes mirroring a product, the concept evolved to include manufacturing processes as subjects of virtual space reproduction (“twinning”) to gain the very same benefits [130]. DT could be best defined as the evolving digital profile of the current and historical behavior of a process or physical object that helps optimize manufacturing performance [182]. It implies that the objective of a DT is to create an exact digital replica of a physical entity, which could be either a process, product, or system. In other words, a DT is the enabling tool of the Industry 4.0 era for proactive organizations or production units that guides them through data-driven decision-making models without triggering potential issues or failures. DTs are well beyond just pure models, they include data, which describe their physical counterparts and decisive action in the manufacturing system based on real-time data [34,132,204].

As digital twin is sometimes used in the context with digital thread, it is necessary to differentiate the DT concept from that of the digital thread. The foundation of digital transformation is a connected enterprise that integrates operational technology (OT) and information technology (IT). This results in a digital thread of information that spans the entire value chain – a seamless data flow from design, manufacturing, to the product life cycle.

A more widely acknowledged definition was given by Glaessegen and Stargel in 2012, who defined DT as “an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, and fleet history, to mirror the life of its corresponding flying twin” [70]. The essence of this definition is to highlight the basic components of a reliable and robust DT model. These components include the physical component, virtual or digital component, and data exchange or communication component (two-way dynamic mapping between the physical component and the virtual or digital component) [230]. These components will be further discussed in detail in Section 3 along with an in-depth analysis of their interconnection.

When it comes to the context of manufacturing systems, DT is defined as: “The DT consists of a virtual representation of a production system that can run on different simulation disciplines that are characterized by the synchronization between the virtual and real system, thanks to sensed data and connected smart devices, mathematical models and real-time data elaboration” [66]. The topical role within Industry 4.0 manufacturing systems is to exploit these features to forecast and optimize the behavior of the production system at each life cycle phase in real time” [66,183].

### 2.2. DT perspective from physical-digital integration

A recent survey has shown that there is no unanimous definition of DT as it is often used synonymously with digital models (DM) and digital shadow (DS) [130]. The main reason for the confusion is the variety of application areas in different disciplines. For example, a digital twin is viewed as a high-fidelity model-based replication of manufactured parts [51]. On the other hand, a digital twin can be recognized based on efficient computational models, enabling real-time process monitoring and control [123]. A classification of DTs has been proposed into three subcategories based on the level of data integration between a physical object and its digital object (Fig. 2). A DM is a digital representation of an existing physical object that has no form of automated data exchange with the digital object. If there exists an automatic one-way data flow from the physical object to the digital object, such a configuration is termed a DS. If further, the data flow between the physical object and the digital object is fully automated in both directions, one might refer to it as Digital Twin [130]. However, reasons for automatic vs. manual data transmission certainly exist in terms of the quality of the data and the timeliness of the data, but that would not change the movement of data in any significant way. Manual or automatic data transmission would not be a differentiator to justify different names and models.

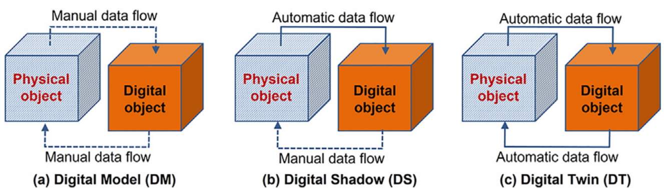


**Fig. 2.** Level of integration between physical object and digital object [130].

The analysis of the state-of-the-art of DT concept shows that the majority of the bulk literature is categorized with the type “concept”, definition, or review without specific use cases [35,130]. However, several use-case studies have been developed at the lower levels of integration for both DM and DS and the relative number of case studies significantly decreases with an increase in the level of integration from DM to DT. There are few DT cases implemented in a laboratory environment. The main focus of recent research on manufacturing DTs addresses manufacturing planning and control as it is the main data reservoir for a manufacturing system that unites all elements together.

### 2.3. DT perspective from the physical asset

A specifically tailored definition of DT and DS from the viewpoint of physical objects (e.g., products, machine tools) has been given in [17]. DT and DS are defined only for real physical assets and not for manufacturing processes, Fig. 3. Therefore, the workpiece, the physical tools (i.e., milling cutter, tool electrode, and forming die), and the machines are real physical objects which possess digital representatives. The manufacturing process itself does not have a DT and DS and can be understood as a transfer function of the mechanical, thermal, and chemical interaction between the physical objects involved which therefore undergo process-related state changes.

There is always only one and no second DT including and combining all relevant properties of the real physical object. Structure and resolution (e.g., the mandatory necessity for real-time data acquisition for time-critical processes) can be application-oriented and must not be universally valid, see [17].

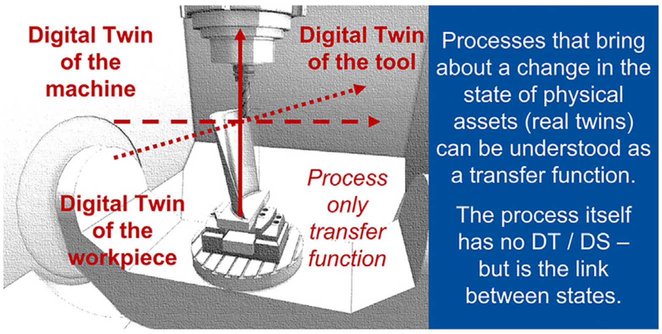


**Fig. 3.** Aachen approach on DT of the workpiece, tool, and machine based on [17].

This so-called "Aachen approach" reviewed DT from a different perspective when applying the concept over the whole lifecycle perspective of a physical product, see Fig. 4. As the manufacturing process itself has no lifecycle and therefore cannot be seen as a real-world asset, the DT of the workpiece could be identified as an according information carrier from the manufacturing phase to the use phase of a real product. The manufacturing process-induced material loads generate material modifications according to the concept of process signature [36]. This will influence – under the boundary conditions of the actual geometry and specific material characteristics – the final resulting part functionality in the use phase, see Fig. 5 [105]. In this context, the tooling (a real physical object like tool electrodes in EDM and ECM) and the machine tool can be recognized as the initial workpiece or assembled part system in the use phase. Therefore, the historical data of all processes involved during the manufacturing phase –

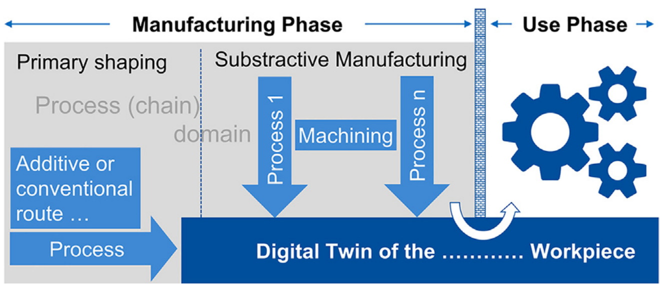


**Fig. 4.** The digital twin of the physical asset as information carrier from manufacturing to use phase with intended overall added value utilization.

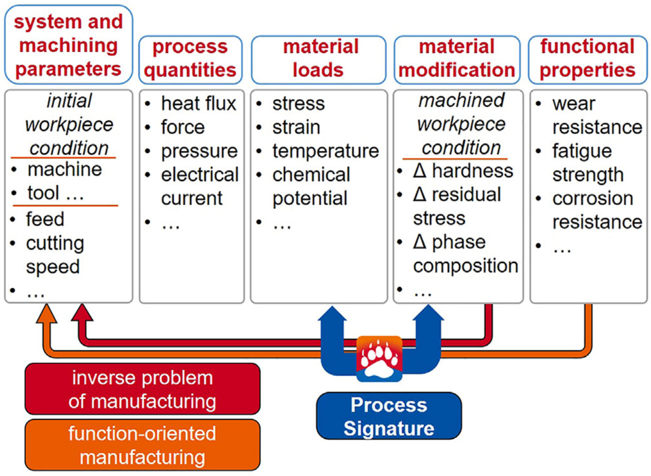


**Fig. 5.** Causal sequence of manufacturing processes, based on [105].

from primary shaping processes (e.g., AM processes and conventional ones) to finishing by subtractive and even non-subtractive operations for changing material characteristics (e.g., heat treatment, shot peening) – are allocated in just one DT which is finally relevant for real applications.

The manufacturing process has not to be mirrored in its own DT, but can be added as individual load history acting on the workpiece, the tool, and the machine. This would avoid the need for unnecessary additional information storage without defined integration in the surrounding production phase and conditions. According to [36], the workpiece and, therefore, the physical asset does not know the process but just feels the loads and reacts accordingly. To comprehensibly describe the temporal and spatial material loads involved in the manufacturing process, a comprehensive process model is still necessary. Only relevant information (in terms of mechanical, thermal, and chemical loads resulting in local modifications) at the interface to the real asset is stored in the DT.

### 2.4. Digital twin evolution

Conceptualization and complexity of DT have been constantly evolving from simulations to DTs over the decades, as depicted in Fig. 6. Today, DT has been projected as an enabling technology that will revolutionize the landscape of the Industry4.0 paradigm, but on the ground level its conceptualization and bounds remain to be defined and its significance in various domains still needs reexamination.

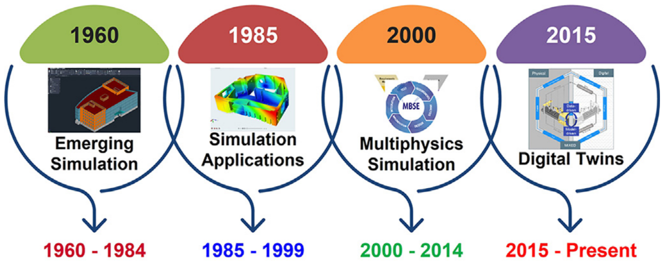


**Fig. 6.** Concept evolution towards DT development (adapted from [132]).

This underscores the fact that DT technology in its full essence is yet to be fully understood. Its depth and breadth are evolving. Moreover, myriad recent research highlights that DTs may not be limited to a single definition [143,204,229]. Rather, the level of integration in existing process/product design and the complexity of applications determines the definition of DT in the context [73]. While a lot of conceptual studies have been conducted for DT, few research papers have demonstrated practical implementation of DT to date. This is a

Please cite this article as: Y. Guo et al., Digital twins for electro-physical, chemical, and photonic processes, CIRP Annals - Manufacturing Technology (2023), https://doi.org/10.1016/j.cirp.2023.05.007

critical research gap because the definition and functional properties of an evolving concept like DT should be directly linked to experimental outcomes [45].

Built on the DT literature review, the Scopus literature databases were searched for all articles, books, journals, or similar relevant materials bearing "Digital Twin" titled publications. Going further back from 2015, only 3 DT-titled research works were published. Nearly 1700 articles (Fig. 7) have come on the scene in 2021. In comparison, DT manufacturing publications started to emerge in 2015. More than 700 articles, books, or journals referring to DT manufacturing have been published in 2021 alone. This trend clearly shows a tremendous increase in the impetus of DT.

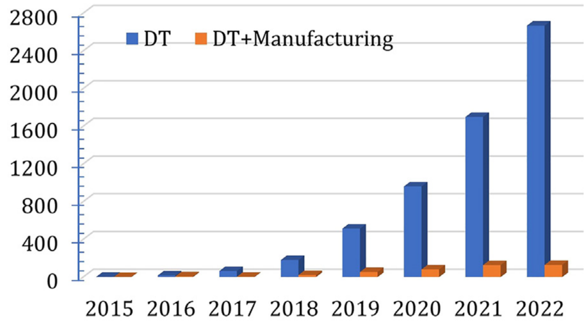


**Fig. 7.** "DT"-titled vs. "DT + manufacturing"-titled publications.

Such astounding figures and ubiquitous coverage suggest that DT implementation has come a long way in various application domains [130,229]. Yet, the reality begs to differ. The latest literature review suggested that, while theoretical conceptualization, definition, and high-level schematics of DT have been widely presented, very few papers/ articles have gone one step ahead to discuss empirical system architecture, data acquisition and transmission modeling, bi-directional communication schema (for software related to CAD/ CAM/FEA or topology optimization), and necessary hardware (sensors, actuators, and base physical systems) that are required to realize a basic level DT (either product or process) [4]. Hence, from the standpoint of future research, it is crucial to identify and segregate literature sources that would provide fundamental building blocks for both academia and industry to explore the next avenues of DT technology [45]. It has been a well-established agreement that the core of a DT lies in the generation, processing, and exchange of information between interacting components of DT-enabled systems. Consistent data generation, interpretation and processing, and universality in the exchanged data format are critical [34,132,204].

DT as a concept has been far more practical and executable for 'systems-of-systems' than it was coined in 2002. Advances in data transmission, resolution, AI/ML, and data-driven MPC have made it possible for manufacturers to leverage DT in reducing design lead times, managing gigantic ecosystems, dynamically re-calibrating, and creating a better production environment through software-driven devices [170]. Fig. 8 clearly shows that in the past two decades, DT has gained a lot of traction, and sustained momentum toward digital transformation will play a crucial role in realizing ubiquitous smart manufacturing.

## 3. Digital twin framework

### *3.1. Digital twin framework for manufacturing processes*

Fig. 9 represents a DT framework for a manufacturing process in the physical domain and its companion twin in the digital domain, which consists of: a) the process or physical object(s) and their environment, b) the digital twin (i.e., digital model), and c) the two-way communications (also referred to as the digital connections) between the two entities.

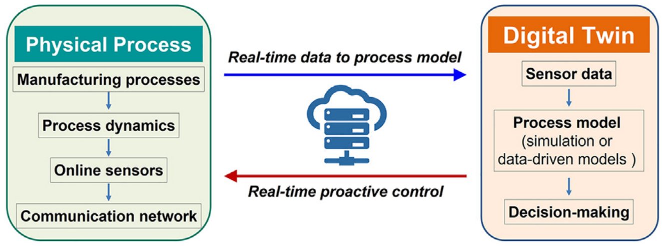


**Fig. 9.** Digital twin framework for manufacturing processes.

The DT serves as a virtual real-time replica of what is happening in the physical process. The DT model provides a mechanism for two-way communication between the physical manufacturing process and its DT. The journey between physical-digital interactivity underscores the profound potential of DTs: various sensors take continuous, nontrivial measurements that are streamed to a DT, which, in turn, performs the real-time diagnosis, prognosis, and control to optimize a process transparently.

The development of a DT involves two main aspects: i) designing the DT process and information requirements, and ii) the creation of the enabling technology to integrate a process or a physical object and its DT for the real-time data flow between the physical world and the digital world. The process DT can be expressed or defined through five enabling components (Fig. 10) – sensors and actuators in the physical domain, integration, data, and analytics – and the continuously updated DT application [187].

The data create/ingestion step encompasses in-situ monitoring of the process, the machine, and its surroundings. The real-time data can be transmitted into a secured digital format using encoders and then fed to a DT. The sensor data may also be augmented with other

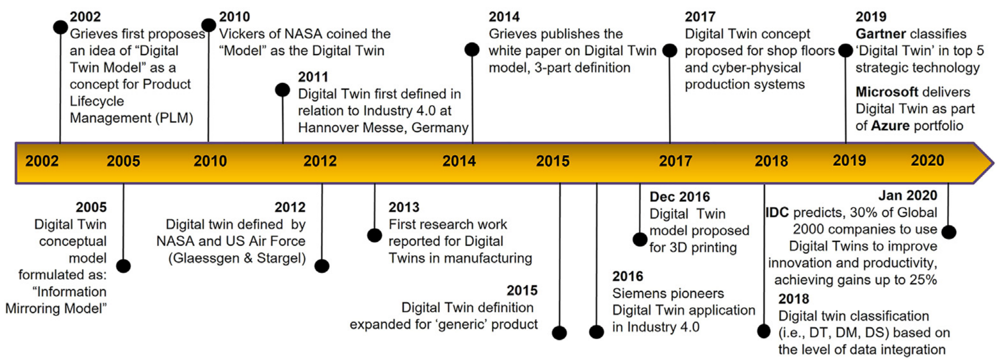


**Fig. 8.** Evolution of DT since its inception.

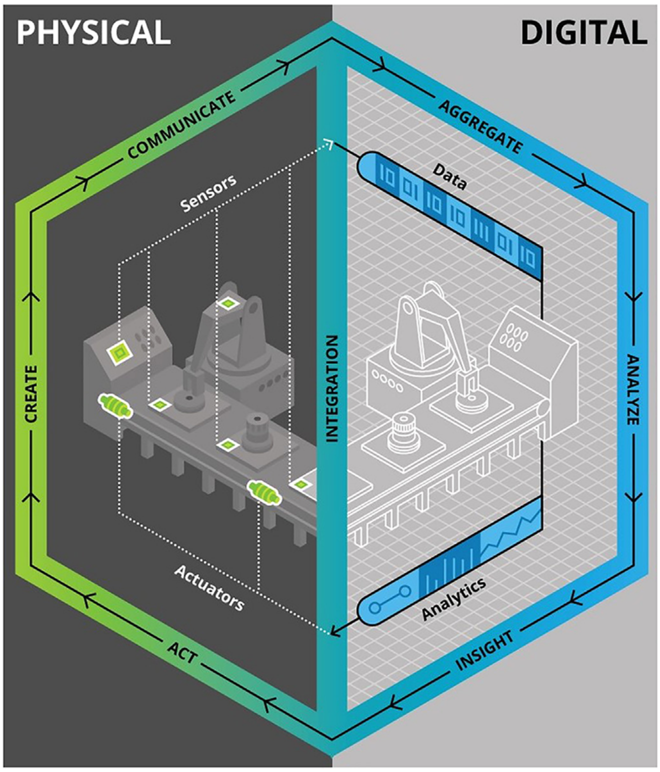


**Fig. 10.** Digital twin constituent elements [187].

information such as the CAD model. This would provide the DT with a stream of contextual data.

The communication step achieves seamless, real-time, bidirectional connectivity between a manufacturing process and a database through three mechanisms: edge/cloud computing, communication interface, and edge security.

The aggregation step curates and integrates the heptamerous data into a federated database in an edge or cloud environment. Edge computing operates on the "instant data" (e.g., real-time data from sensors and computer numerical control (CNC) controller) and provides execution resources with sufficient connectivity close to users on the factory floor.

The analysis step involves advanced data analytics approaches (e.g., AI/ML) or physics-driven ML approaches for model predictions. The models driven by the "instant data" data may incorporate process dynamics to generate real-time insights and recommendations for decision-making.

In the insight step, insights from the data analytics are visualized and highlighted on dashboards or edge devices for monitoring and identifying process anomalies.

The act step is where actionable insights/decisions can be translated into actions back to the physical manufacturing process. Insights/decisions pass through programmable logic controllers (PLCs) and are fed into the actuators of the machine to adjust process parameters in real-time. This proactive control completes the closed-loop connection between the physical asset and the DT.

## 3.2. Process models: building blocks for DTs

Models are core assets of DTs in manufacturing processes. The role of models in a DT is to analyze, predict, and optimize process behaviors. Process models are in the form of analytical, simulation, or data-driven formats. In the mentality of the general public, a simulation model is often regarded as a DT. However, DT is well beyond simulations and data-driven models. For a process-related DT, the non-realized or neglected two-way communication between the process and the process model will lead to missing the key feature of a DT, which will reduce the DT to DS.

### 3.2.1. Physics-based simulation models

Physical process models serve a three-fold purpose: (a) understanding the process nature and its basic characteristics; (b) generating the complementary data which cannot be measured otherwise, and (c) developing a model-based predictive controller for manufacturing process control. Traditional analytical and/or mechanistic models have been developed for various manufacturing processes based on process mechanics (e.g., static or dynamic mechanistic models). However, these models (either analytical or numerical models) have an inherent bias due to their assumptions or incomplete physics underlying complex manufacturing processes [77]. With the increasing high-performance computing, physics-based white box numerical simulation modeling (e.g., finite element models/FEMs) becomes a dominant approach. However, the accuracy of the simulation models is limited due to the assumptions or simplifications made for model derivation. In particular, simulation models require calibration of model constants when process dynamics change (e.g., tool wear in cutting, melt pool instability in metal AM) and are too computationally expensive to be used in real-time prediction [77,104]. Also, simulation models may not leverage the rich real-time process data collected from online process monitoring, which reflects the process dynamics.

### 3.2.2. Reduced order models (ROM)

The runtime of simulation models should be close to real-time in a DT setting. One key issue for physics-based simulation models is that they need expensive computation resources, and the computation cost is too high (hours to run) to be real-time (e.g., minutes or seconds) for process control. The computation time of a simulation model can be significantly cut down to real-time in a DT setting through the ROM techniques [102,261].

The common scenarios that call for ROM include (a) massive data to analyze, (b) process physics with uncertainty, (c) known process equations with non-trivial solutions, and/or very high computation time is resource intensive.

ROM represents a cluster of methods to transform a complex, time- and resources-consuming simulation model into a significantly simpler system through both intrusive methods for known system equations and nonintrusive methods [44,58,95,248] for both known and unknown equations. Among the different techniques available for ROM generation, a posteriori or non-intrusive technique has great potential, especially integrated with real process data. These order reduction methods are purely data-driven when compared to data-driven ML models.

CAELIA™ has been proven to be an enabling toolset for ROM generation and management using the tensor-rank-decomposition (TRD) technique [262], which translates a coupled multi-physics simulation into a sequence of products of separable 1-D functions that can be solved on the fly.

### 3.2.3. Data-driven models

In the era of massive or big data, an unprecedented amount of manufacturing data has provided unparalleled opportunities as well as demands for data analytics [65]. ML, due to its learning capability and structural compatibility with advanced computing, has become one of the most advocated methods in advanced manufacturing. In recent decades, ML has gained prevalence in manufacturing industries as a means of process modeling and optimization [67]. The massive data in manufacturing applications, due to advances in sensing methods, reduced cost of sensors, and computing infrastructure, has enabled intensive exploration of ML.

ML is "data-driven" and can converge to models that characterize domain "rules" and that enable decision-making in high-dimensional input space. At the methodology level, ML is related to statistical analysis, which is the traditional pillar of data science, but distinct in objectives – instead of making inferences about the population (like statistics does), ML seeks the general predictive patterns in data [38] and utilizes them to support future decision-making. ML also differs from data mining despite their overlaps in methodology, as the latter emphasizes knowledge discovery from data [85] rather than predictive decision-making.

The key advantage of the data science (DS) methods is the capability of processing the high dimensionality, heterogeneity, and big data and incorporating the in-process uncertainties for efficient discovery of patterns and knowledge. However, their "black box" nature [43,77,156,241] has been criticized for lacking physics understanding, and the ML models need to be carefully trained using massive data – with inevitable measurement errors, limited interpretability, and poor applicability, generalizability, and transferability for other process conditions.

### 3.3. Process control

Process control makes the leap from a DT to action in the physical process through real-time control – that constitutes the essence of being smart. When DT-based decisions are translated into actions, the ultimate goal of predictive models can be formulated as an optimal control problem. As described in the process-DT loop (Fig. 9) the back from DT to the physical process – from process models to actions in the physical manufacturing process through control – constitutes the essence of DT manufacturing. The uncertainty in manufacturing process models (e.g., tool wear in machining and powder variation in AM) cannot sufficiently be taken into consideration in current adaptive control systems [9,223]. A model predictive controller (MPC) is an intuitive control algorithm, which requires an accurate process model of the dynamic behavior to predict future behavior [223]. In particular, the unknown nonlinearities and rapid dynamic behavior in a manufacturing process are challenging to control, but crucial for product quality, productivity, and safety. Furthermore, model coefficients for a nonlinear dynamic state must be adapted when the process state changes. But the determination of specific coefficients is expensive in both time and effort. Most approaches are far from being real-time or online capable [9]. Accurate process models are often assumed known and model parameters are kept constant during the entire manufacturing process [9,147,223]. These assumptions certainly cannot meet the requirements of nonlinear process dynamics and uncertainties for future needs.

The principle of MPC is to determine an optimal pointwise control policy through online optimization [202]. The optimization problem associated with the MPC algorithm can be solved against new measurements, thus resulting in updated control input at each sampling time. The key advantages of MPC are its ability to adapt to process variation and handle hard input/output constraints. A potential drawback of MPC schemes is to calculate the control gain online [16]. Although effective linear programming (LP), quadratic programming (QP), and linear matrix inequality (LMI) solutions based on active sets or interior points are available, calculating control input still requires a lot of online computing resources.

Data-driven models (e.g., ML) may effectively harness the massive online data and incorporate the process dynamics into MPC for improving control accuracy and robustness [9,56,96,104,223]. Nevertheless, the computational cost (i.e., storage and computation) is usually very high for a learning control method, in particular, if deep learning (DL) is adopted.

### 3.4. Digital twin-enabling components

#### 3.4.1. Sensors – data ingestion

Data is the lifeblood of DT, and sensors of many and varied types (e.g., accelerometers, dynameters, IR cameras) provide the needed data at the process, machine, and factory floor levels. The IoT sensors are reviving up DTs. IoT enables connected machine tools and devices to share data with their DTs and vice versa. That is because DTs are always on and are always representing up-to-date simulations or ML models of IoT-connected manufacturing processes they represent. DTs are virtual replicas that may capture the changing process conditions internally and externally in real-time, as measured by myriad connected sensors and devices driven by cloud or edge computing. They can also run ML and/or simulation models in the virtual environment to predict, make recommendations, and test the solutions for improvements through service updates.

The requirement for digital transformation drives increasingly affordable smart sensors with data storage and wireless communications capabilities [161]. Smart sensors may integrate microprocessors and functions of memory, diagnostics, self-calibration, and connectivity. They can collect and store data, and perform certain data analyses, thereby identifying anomalous data. The data can be communicated and used to assist operator decisions, production planning, and maintenance schedules instead of manual data collection [5,161].

A rapidly growing sensor type is the wireless sensor which provides process information remotely and is flexible [205]. If a plant has wireless communications which could be simple and similar to home Wi-Fi, wireless sensors would be easy to deploy. Industrial controllers combine data collection, data analytics, control, and alerts for use with the sensors. The maintenance requirements of the sensors also need to be considered.

#### 3.4.2. High-speed communications

Digital twin manufacturing requires fast, reliable, and (preferably) wireless data transmission systems for real-time monitoring and control of time-critical processes with very challenging requirements in terms of low latency, reliability, and determinism [205]. Current factory floors are dominated by wire-bound Ethernet networks and/or wireless (e.g., Wi-Fi) [2].

Traditionally, the sensor data streams have been sent securely and with high integrity via hardwire in the factory environment. As digital transformation advances, the use of sensors and other sources of data will be relied upon at an increasing rate. The cost and physical space to physically connect this equipment cannot be economically and efficiently done with hardwiring. A wireless solution that allows flexibility, mobility, and lower installation complexity and associated cost is a required substitute.

Manufacturers are looking to adopt emerging wireless technologies into their facilities to benefit from communication protocols such as 5 G and 6 G, Wi-Fi 6, Ultrawideband (UWB), and other protocols [125]. The emerging wireless communication technologies will achieve high throughputs, ultra-low latency, and high reliability [1,2,205] to facilitate real-time process control.

#### 3.4.3. Data curation and integration

Manufacturing process data is not only heterogeneous (CAD data, sensor data, production data, simulation data) but also massive [167]. The data can be categorized into structured data (e.g., process parameters) and unstructured data (e.g., time-series and image data). However, simply putting all the data into the same repository would not make the data actionable to drive a DT [177]. An information management system consisting of data standardization, placement, discovery, integration, and interoperation will overcome the inefficiencies caused by the current data management shortcomings.

First of all, data integration is the key to ensuring data is interoperable [56]. With data integration, potentially related datasets can be found and linked together. Scripts (i.e., code or programs) can be automatically generated to connect the related datasets. Content similarity, syntactic similarity, and semantic relatedness can be leveraged to find related datasets. Datasets with large enough similarities are considered related. DL techniques may be used to measure semantic similarity. Program synthesis techniques [75] could be used to automatically generate scripts/codes/programs to join related datasets.

Second, data discovery is one of the most fundamental barriers to effective data sharing [60]. A data catalog can be built for all the data in the data warehouse. Each entry in the data catalog corresponds to a dataset in the system and contains the physical location and metadata of the dataset [175]. The data catalog, as well as the original datasets, may be indexed to provide multiple interactive, self-service data discovery functionalities such as dataset recommendation and browsing by categories. Also, with data integration, a system can create linkages between related datasets. These linkages can be used in data discovery and exploration to diversify query results.

Third, data standardization and normalization are very essential. Data generated by different sources might have different formats and standards. To improve data usability [98], batch editing, constraints, normalization, and error detection and repair can be used to materialize data standardization. Transformation rules can also be learned from user edits and applied to other applicable entries. In addition, implicit constraints may be mined from existing data and explicit constraints can be specified by the users.

In addition, edge computing [214] operates on “instant data" and provides execution resources with sufficient connectivity close to users on the factory floor. The major benefits of edge solutions are low latency, high bandwidth, and safe computing and storage, which are particularly important for real-time process control. Holistic data architecture and algorithms are critical and highly needed to curate and integrate these multimodal data at the edge for subsequent real-time data analytics and process control.

## 4. Digital twins for energy beam processes

### 4.1. Metal AM

Metal AM processes, including powder bed fusion (PBF) and directed energy deposition (DED), involve intense Marangoni flow, steep temperature gradient, high cooling rate, and intrinsic cyclic heat treatment which are not encountered in conventional manufacturing processes (e.g., casting). Attempts to develop DTs of metal AM processes aimed to recapitulate key phenomena during the printing process, e.g., energy-material interactions, heating, solidification dynamics, phase transformation kinetics, development of defects, residual stresses, and distortions, which are fundamental to understanding microstructure and part properties (Fig. 11); or in the case of the vat-photopolymerization process the curing kinetics including the variation of glass transition temperature and vitrification [198,231].

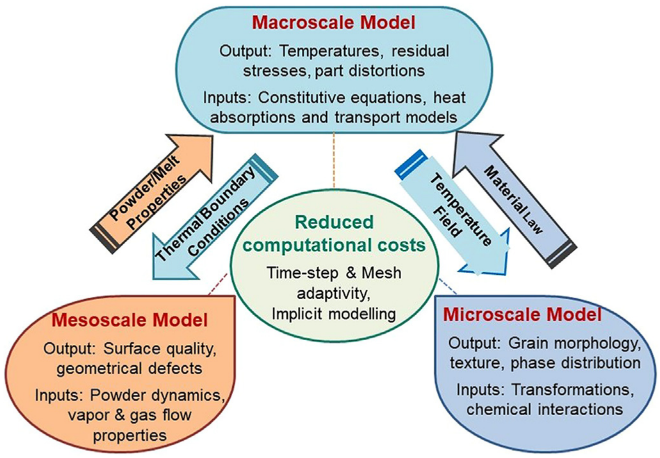


**Fig. 11.** Key DT building blocks for metal AM (adapted from [171]).

However, the development of proper process models is not a trivial task due to the complex relationship between material-process-microstructure-property as shown in Fig. 11. Table 1 summarizes the current physics-based multiscale simulation methods, and their applications in metal AM processes. The following sections summarize the modeling methods at different AM process stages from powder spreading, rapid melting, and fast solidification [144,164,173,184]. Alternatively, pure data-driven ML models are also emerging.

#### 4.1.1. Powder spreading

The DEM method aims to simulate a cluster of discrete particles and the translational and rotational motions of an individual particle by incorporating their size distributions [251,271]. For the deposition of powders, different types of forces are modeled on the individual particle [64], e.g., wall force due to contact with constraining surfaces, adhesive bonding force, damping force caused by the surrounding environment, and electromagnetic force, respectively.

**Table 1**
Simulation methods and applications in metal AM.

| Simulation Methods | Process Phenomena | Process Physics |
|---|---|---|
| Discrete element method (DEM) | Powder spreading | Particle dynamics |
| Computational fluid dynamics (CFD) | Powder melting | Thermal fluid dynamics |
| DEM-CFD | Powder packing-melting | Particle & thermal fluid dynamics |
| Lattice Boltzmann method (LBM) | Powder packing-melting | Thermal fluid dynamics |
| Phase field (PF) | Solidification | Phase dynamics |
| Cellular automata (CA) | Solidification | Phase dynamics |
| Finite element method (FEM) | Workpiece cooling | Heat transfer |

The feasibility of DEM has been shown for powder-based metal AM [271]. The DEM method has been further applied in several AM processes [81,188,224] (e.g., Fig. 12). The key problem of DEM is that particle fusion and plastic deformation may not be modeled. A coupled DEM-CFD model can be extended to solve the problem.

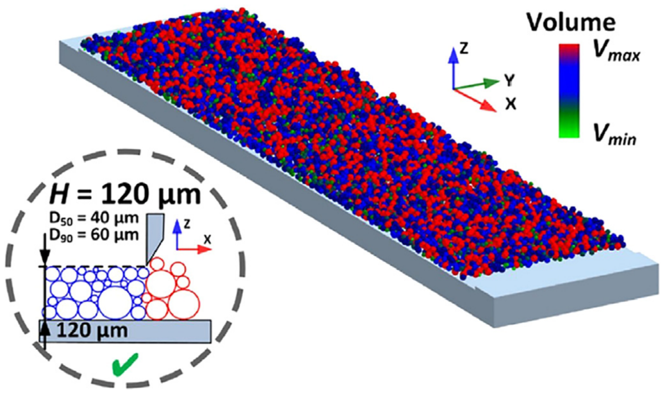


**Fig. 12.** Powder packing state under gap height 120 $\mu$m [250].

#### 4.1.2. Powder melting

The melting pool is the key element of DTs of metal AM. Many CFD models have been developed by incorporating the Navier-Stokes equation with the energy balance equation to understand and predict the melt-pool behaviors (e.g., temperature, velocity, pressure) at the microscale [50,78,146,186,234,237]. A 3-D CFD model has been developed to simulate a multilayer DED process with coaxially fed powders (Fig. 13) [164]. Heat transfer between the powders and laser beam was modeled during their flight between the nozzle and the growth surface and after they deposit on the surface. The geometry of the deposited layers measured from the experiments was compared with that predicted by the model. The spatial variation of melt pool geometry, peak temperatures, and cooling rate was examined in all layers. A good agreement was achieved between the computed geometry, cell spacings, and hardness with the experimental data. However,

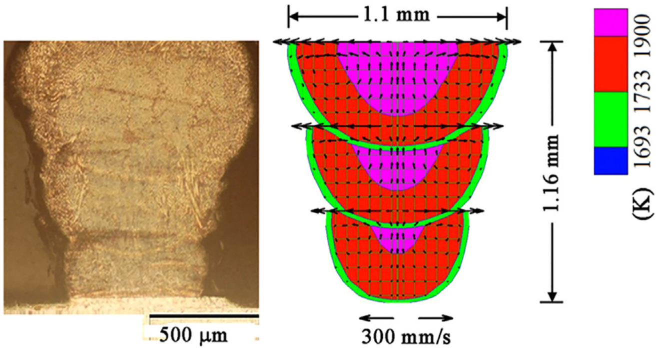


Fig. 13. Multiscale full process model for DED [164].

most studies assumed several simplifications, e.g., 2-D approximations, 3-D calculations ignoring convective heat transfer, and 3-D convective studies assuming a flat top surface. Recently, progress has been made to model the free surface profile using either the level-set method or the volume of fluid (VOF) method (Fig. 14).

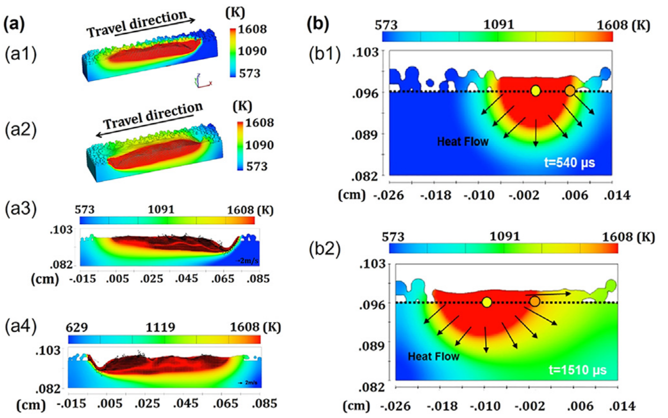


Fig. 14. (a) 3-D longitudinal section of temperature fields: (a1) and (a3) are at the end of fusing the 1st track, and (a2) and (a3) for the 2nd track; b) 2-D vertical section of temperature fields (adapted from [144]).

A novel CFD model has been proposed for laser-based PBF (L-PBF) to study the evolution of the surface morphology of the melt pool with the driving forces of the Marangoni effect and steam recoil during pulsed L-PBF [269]. The results show that a longer exposure time produces greater recoil pressure and sufficient molten liquid, resulting in a more crowded fish scale pattern, as shown in Fig. 15. The recoil forces, Marangoni, and surface tension forces have also been studied in L-PBF (Fig. 16) [234].

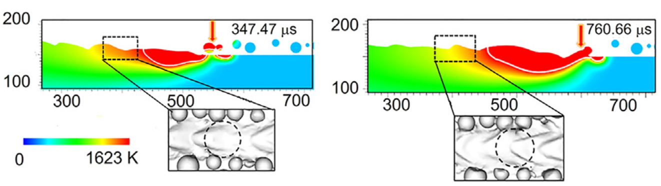


Fig. 15. Evolution of molten pool morphology (adapted from [270]).

The LBM method has been applied to simulate melt pool dynamics in metal AM processes [8,61,127,128,168,200,259]. The thermal model with a Gaussian-type heat source and the hydrodynamic model are often used in LBM [127,259]. For PBF, the surface heat source model is often used because a large fraction of the laser intensity is reflected and most laser energy is absorbed on the surface [61]. The flow in the melt pool is driven by

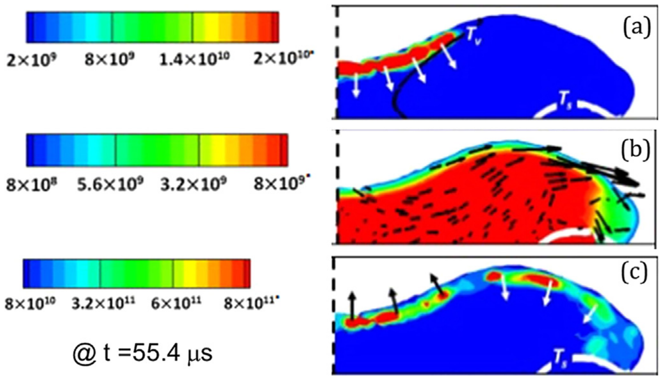


Fig. 16. Contours of the recoil force (a), Marangoni force (b), and surface tension force (c) [234].

capillary, Marangoni forces, recoil pressure, and the wettability of the powders. Several LBM-based simulations have been developed by incorporating free surface boundary conditions, surface tension, phase transitions, and wetting. e.g., wall formation (Fig. 17) in an electron-beam based AM process [8,128,168,200].

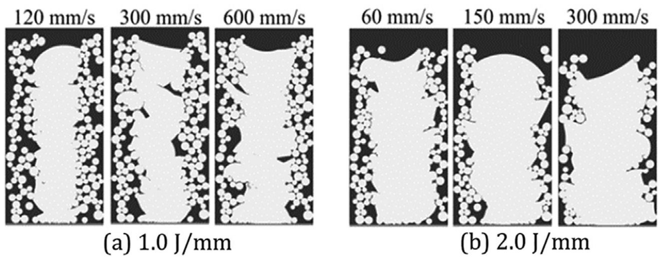


Fig. 17. Wall formation as a function of beam velocity and line energy [128].

### 4.1.3. Solidification

The solidification model is another key element of a digital twin of any PBF or DED system. Numerical approaches, including Monte Carlo (MC) [176,203], Phase Field (PF) [6,106,133], Cellular Automaton (CA) [7,124], and its modified method [191], and Dendritic Needle Network (DNN) methods [233] have been developed to simulate the grain morphology evolution during the solidification process. Although each of these methods has its pros and cons, the common challenge is that these methods are computationally expensive which limits their applications to relatively small tempo-spatial scales.

The solidification texture of IN 718 fabricated by DED has been investigated and showed the differences in solidification textures under the effect of local temperature fields due to the different scanning strategies [244]. The solidification texture is influenced by the directions of local heat flow and the competing grain growth in preferred growth directions which depends on the crystal structure alloy. The numerical model has shown that the primary dendrites form a 60° orientation with the horizontal direction (Fig. 18a-b) in unidirectional laser scanning. For bidirectional laser scanning (Fig. 18c-d), the angle between primary dendrites of neighboring layers was about 90°

The solidification mechanism under complex boundary conditions imposed by electron beam melting (EBM) (Fig. 19) has been investigated in [52] and [199]. These studies demonstrated the ability to induce site-specific microstructures within a given part configuration and highlighted the ability to use DTs for customizing solidification textures during the AM process. The effect of thermo-mechanical cycles on substrate warping and residual stress during EBM has been investigated using ABAQUS [195]. In this case, additional coarse-graining has been performed to lump several successive layers.

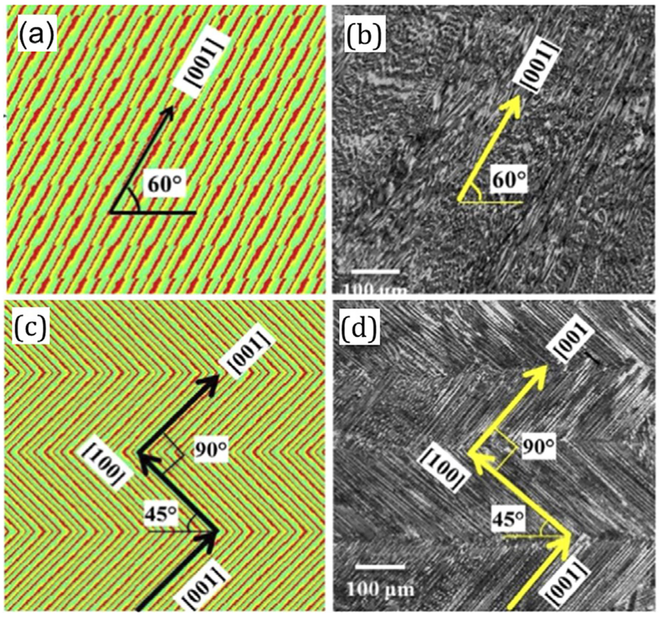

**Fig. 18.** Solidification texture depending on scanning patterns [244].

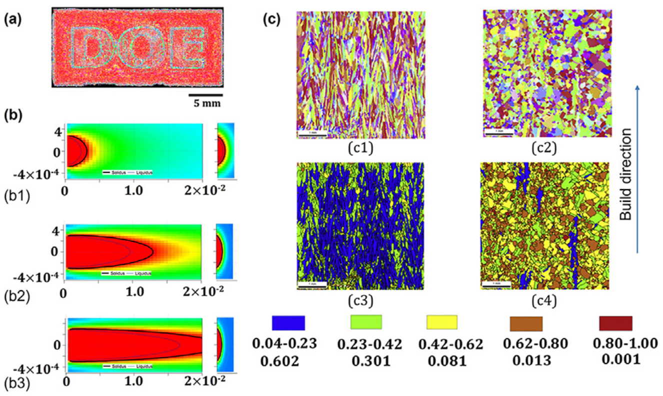

**Fig. 19.** Site-specific microstructures in EBM (adapted from [52,199]).

The CA method has been leveraged to simulate the columnar grains (Fig. 20a) in the traverse cross-sections during a single deposition track. The dependence of grain morphology on process parameters has been studied during the EBM of IN718 by tracking the magnitude and direction of the simulated temperature gradients [129]. The columnar grain structure evolved to the equiaxed grain structure when changing the scan speed from 2.2 to 8.8 m/s and the hatching offset from 150 $\mu$m to 37.5 $\mu$m at laser power 594 W. A 2-D coupled LBM-CA model has been developed to study the impact of melting strategies on the final grain morphology [200]. The coupling effect was modeled by interchanging the phase state information and the current temperature field. The LBM model provides the temperature information which drives grain growth, while the CA model provides the phase information to the LBM model. An example of the simulated columnar grain in a multi-layer deposition is shown in Fig. 20b).

A coupled DEM-CFD model has also been developed to simulate a multi-layer deposition process in L-PBF [14,243]. The geometrical information of the metal-gas interface was extracted from the simulated results of the CFD model and fed into the DEM model as a boundary condition for next-layer deposition. The molten pool data, such as the fields of temperature and metal fraction, was also extracted and then interpolated to re-initiate the computational domain of the CFD model. By repeating the process, the multi-layer LPBF process can be simulated successively. The model combination mechanism is shown schematically in Fig. 21.

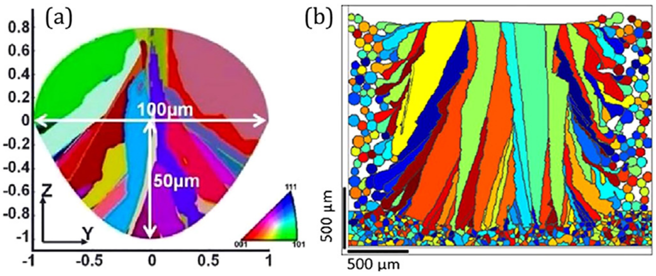

**Fig. 20.** Simulated columnar grains traverse cross-sections: (a) single deposition track [191], (b) multi-layer deposition [200].

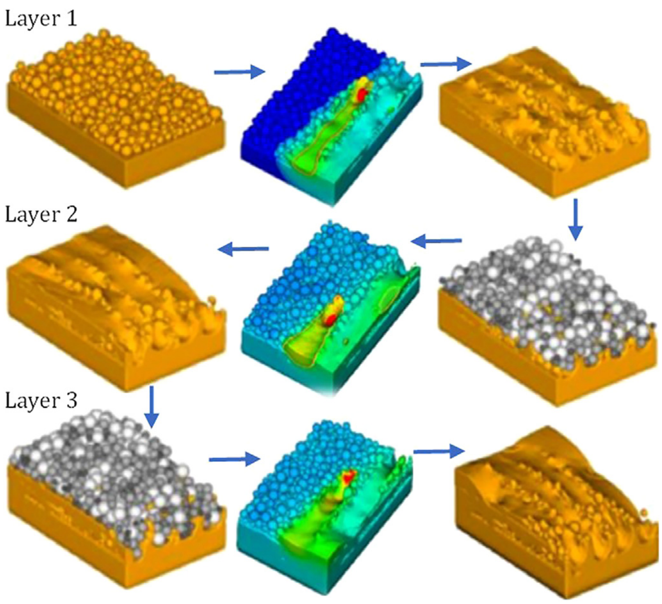


**Fig. 21.** Coupled DEM-CFD model for multi-layer deposition (adapted from [14]).

*4.1.4. Residual stress*

The unique rapid heating-melting-cooling thermal cycle of metal AM causes high residual stress during and after processing. The residual stress-induced part distortion may damage the recoater blade during an AM process and dramatically deteriorate the functionality of the final parts. The steep temperature gradients are the underlying mechanisms for residual stress formation [172].

One technical route to predict microscale residual stresses is computation-intensive fully coupled thermo-mechanical FEM which requires no calibration; for example, the software package Netfabb. Macroscale residual stresses have been modeled through a multi-layer build-up process using the element "birth and death" technique [53]. The temperature-thread [145] method can be used to speed up the lay-building process in L-PBF for efficient FEM modeling. The presentative predicted results are shown in Fig. 22.

The other technical route to predict residual stresses is through the inherent strain method [258]. However, a calibration step is required to capture the inherent strain developed for a combination of machine, scan process, and material. Several commercial software packages, including Amphyon, Simufact, and Additive Print, belong to this technical route.

The influence of thermo-mechanical cycles during EBM on residual stress and distortion of the substrate has been investigated using ABAQUS (Fig. 23) [195]. In this case, coarse-graining has also been conducted to lump several successive layers.

*4.1.5. DTs: beyond process simulations*

A process simulation is the core component of a DT, but they are two very different things. A DT uses simulation models to not only produce information about how a process or product will perform in the physical world under a wide variety of conditions but also how

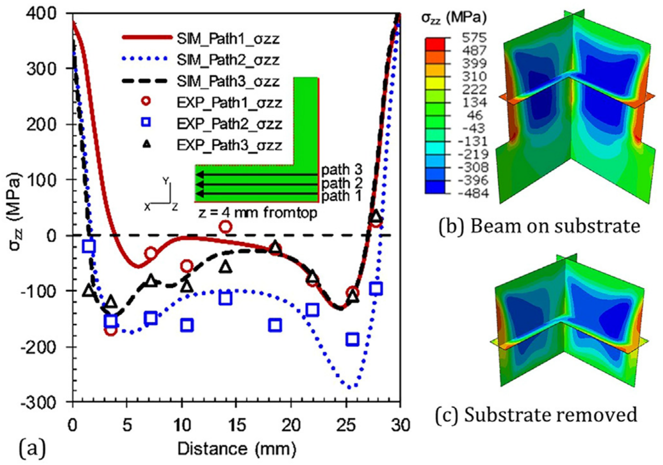


**Fig. 22.** Predicted residual stress of the beam: (a) along paths 1, 2, and 3 along X direction: (b) beam on the substrate, (c) substrate removed [145].

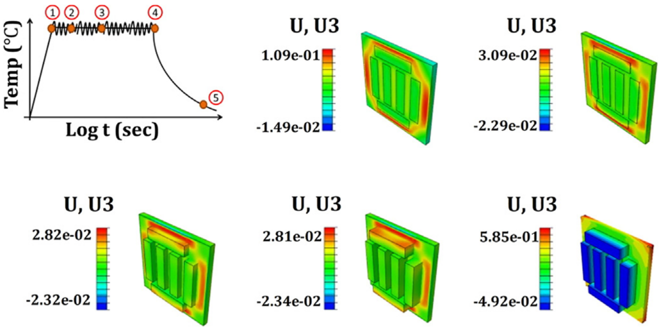


**Fig. 23.** FEA modeling of substrate distortion with simplified temperature input to quantify displacement at various stages of processing (adapted from [195]).

that performance will change throughout its value-chain or lifecycle. Simulations can be performed on DTs of the existing processes or products. However, simulations can be performed on processes or products under development to validate that a new process or product will meet its requirements once it is physically manufactured.

Despite the significant developments of process models to describe the morphological transformations of the materials during the printing process and post-printing consequences (e.g., residual stress, distortion), previous models do not allow the complete virtual description of the entire production process. The data-driven and physical simulation models were combined in a DT for the prediction of the geometry of single tracks produced by LMD [87].

Besides AM processes, DTs for AM must be able to incorporate design, inspection, and evaluation aspects integrating data analytics and AI engines for decision-making (Fig. 24).

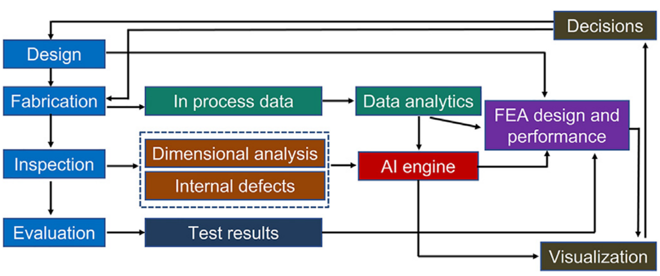


**Fig. 24.** DT for the entire AM production process (adapted from [87]).

Recently, a generalized framework has been proposed for an AM process DT, which can be applied to different AM processes (Fig. 25) [76]. For the prediction of mechanical properties, imaging techniques and augmented reality (AR) were used to predict

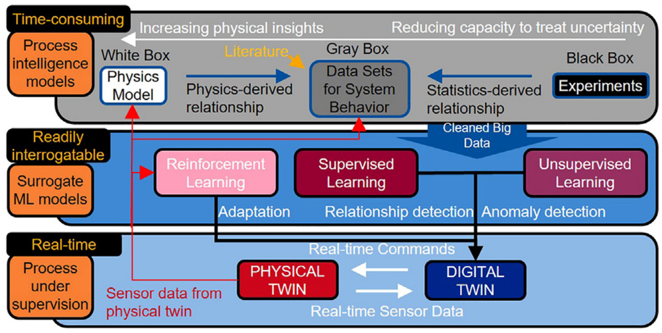


**Fig. 25.** Simplified representation of the ecosystem of a process DT (adapted from [76]).

the localized properties of PBF parts [212]. Similarly, X-ray computed tomography (CT) was used to investigate the effect of the L-PBF scanning parameters and strategies on the distribution and size of pores within the printed parts [54]. The anisotropy of mechanical properties in extruded parts has been studied using imaging techniques for optimizing printing paths [148].

DT frameworks have been proposed to control specific process parameters such as gas flow [109] or temperatures [63]. A DT-driven data management framework has been proposed for metal AM processes to enable the development of advanced data analytics, which allows the implementation of intelligent process monitoring, control, and optimization (Fig. 26) [150]. In this model, the cloud DT communicates with a distributed edge-based DT at different stages of product lifecycle. A hierarchical DT framework (Fig. 27) was also proposed with four distinct levels, which provides a unified ontology for the unique needs of metal AM [193].

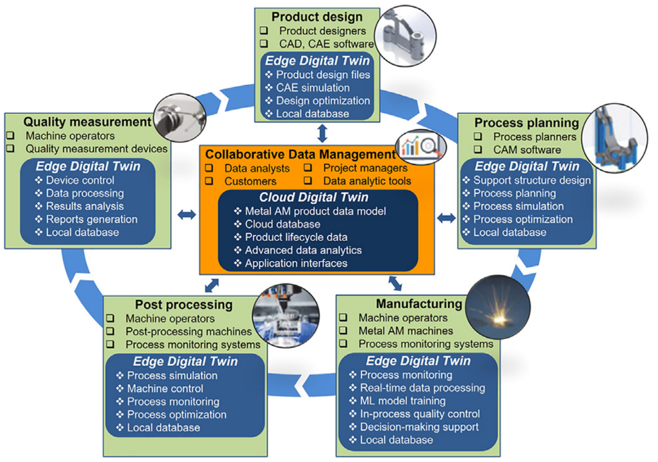


**Fig. 26.** Conceptual framework of a digital twin to enable collaborative data management (adapted from [150]).

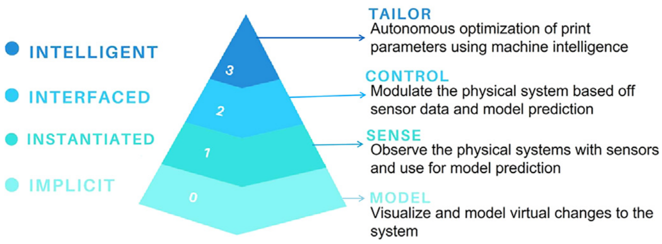


**Fig. 27.** Hierarchy of a metal AM digital twin (adapted from [193]).

## 4.2. Polymer AM

Several mechanistic and phenomenological models have been proposed to simulate photocuring reactions in stereolithography (SLA). Several phenomenological models have been developed to simulate the curing kinetics in laser-based and mask-based SLA systems [11-13,169]. The models include the effect of key material properties, e.g., photo-initiator concentration and viscosity and the effect of light intensity. Morphological development analysis was conducted using models determining the variation of glass transition during the photo-curing process, which allows predictions related to the need for post-curing. The models, developed for the free radical photopolymerization process, are also able to predict the overall shrinkage of printed parts.

Post-curing models have been also developed. Recently, a phenomenological model has been used to simulate the shrinkage anisotropy phenomenon that occurs during the sintering process of previously cured highly reinforced resins [163]. It demonstrated that the phenomenon is caused by non-ideal particle packing between the successive printed layers. Based on this finding, a sintering model has been developed for the prediction of the sintering anisotropy. The model also allowed the prediction of part dimensional changes during sintering.

A predictive model has been developed to assist in the design and manufacture of structures produced through photopolymerization based on inkjet printing using photoreactive liquid inks and photopolymerization (Fig. 28) [268]. The model simulates the curing kinetics as a function of critical process parameters such as UV source pathway, UV intensity, printing strategy, and inter-layer attenuation.

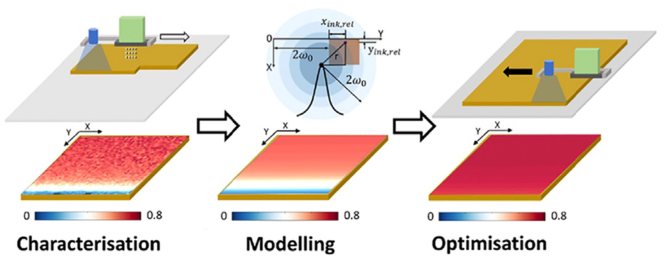


**Fig. 28.** Degree of vinyl group consumption [268].

For fused deposition modeling (FDM), a DT has been designed and developed by integrating the modules of quality evaluation, compensation of printing effects, and monitoring and control for improving system reliability, monitoring the process, and optimizing the process ultimately [181]. Fig. 29 shows the DT architecture, to highlight the information flow between the physical and the virtual environments.

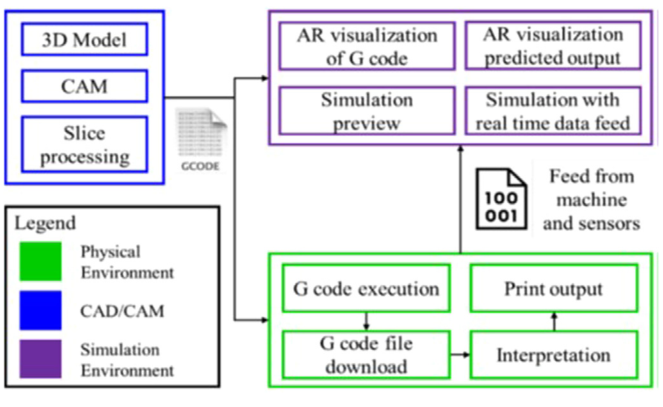


**Fig. 29.** DT architecture data-processing for FDM [181].

In extrusion AM, the molten polymeric material is deposited on a platform and starts to solidify while cooling down. The layer-by-layer build-up process of consecutive layers introduces heat treatment of the previously printed material, generating a complex thermal cycle with a significant influence on the material properties of the printed scaffolds. Therefore, the accurate prediction of the thermal cycle is essential to design and print polymer scaffolds and the bonding between the layers. A novel multi-stage predictive model has been developed by coupling a 2D representation of the dynamic printing process and a 3D thermal model to simulate the deposition process [254]. The simulations have shown how the deposition velocity controls the spatial dimensions of the individual deposition layers and the cooling process when consecutive layers are deposited during printing. Moreover, the numerical results show that the model predictions are consistent with the experimental data. Numerical models were implemented using the ANSYS Workbench software (ANSYS, US) and conducted using a multi-phase model in terms of energy and thermal equations with the assumption of an incompressible and non-Newtonian material. The models are capable of simulating both temperature history and dimensional characteristics of filaments during an extrusion process (Figs. 30 and 31). The different simulation scenarios were experimentally extruded using a 3D-BioPlotter (Envisiontech, Germany), and the temperatures were measured using thermal imaging through a thermal IMAGER TIM 160S (Micro-Epsilon, UK).

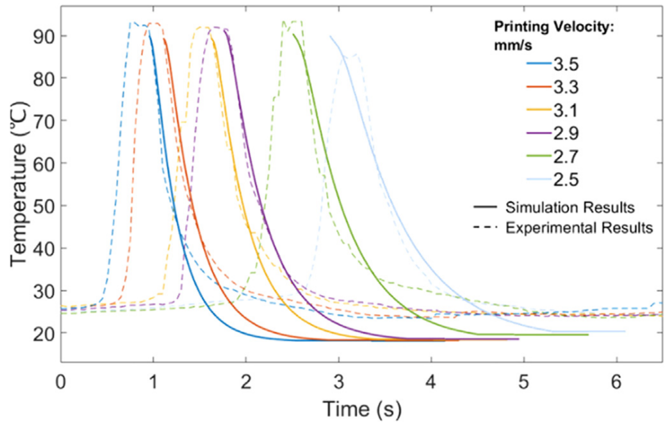


**Fig. 30.** Comparison between numerical and experimental thermal imaging results of the temperature history for the one-layer filament case [254].

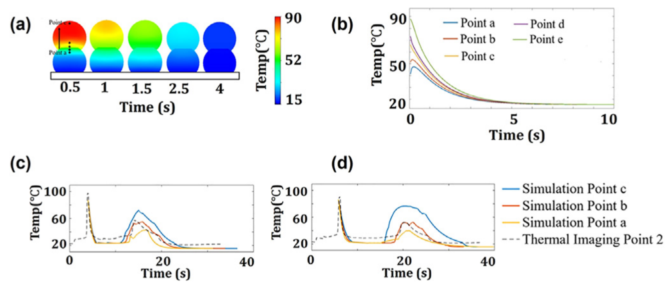


**Fig. 31.** Temperature results of a two-layer filament model with $v_e = 3.5\ mm/s$ and $v_p = 3.5\ mm/s$ (a) section view of the filament temperature distribution at different times, (b) relative temperature cooling profile at different positions (time measured from the end of the deposition of the 2nd layer). Vertical temperature variations and thermal imaging of case with (c) $v_e/v_p = 3.5/3.5$ mm/s and (d) $v_e/v_p = 3.5/2.7$ mm/s (time corrected to the corresponding experimental time) (adapted from [254]).

For filament-based extrusion processes, an analytical model has been developed to compute the minimum force necessary to push the filament into the extruder according to the process parameters [192]. The model accounted for the contributions of both the deposition force and the extrusion force. This will allow the prediction of the variation of the required pushing force when the layer height varies.

The impact of printing conditions on the behavior of shape-hanging parts (4D Printing) was investigated [267]. Parts were produced using vat-photopolymerization and methacrylate resins and, as described, scan speed and layer thickness have a considerable impact on the shape-changing performance. The proposed model allows, not only for prediction with high accuracy fixity and recovery cycles but also to tailor the shape-changing performance by changing processing conditions.

Electrohydrodynamic (EHD) inkjet printing is an AM process that like electrospinning, which can be characterized by the creation of a stable Taylor cone. Printed filament diameters, which are proportional to the jet thickness, are determined by key processing parameters such as applied voltage, nozzle-inlet velocity, and distance between the nozzle-platform. Therefore, for each specific material, process optimization is a complex task. A multiphysics model has been developed using COMSOL by coupling the electric and hydrodynamic fields followed by using the level set approach to tracking the air-liquid phase boundary [189]. A stable Taylor cone can be achieved using suitable boundary conditions and parameter magnitudes. Similarly, a CFD model has been developed to investigate the cone-jet printing process including cone formation, jet generation, jet break, and droplet expansion (Fig. 32) [100]. The CFD model allows for determining the operating parameters for a specific printing resolution given a new material formulation, thus minimizing the need for extensive and expensive experimental tests.

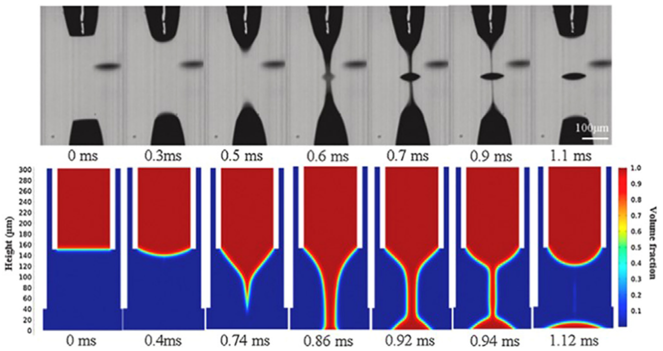


**Fig. 32.** The simulation and experiment validation of the droplet generation process (Voltage is 800 V, the pulse frequency is 20 Hz, the duty ratio is 1%, and the flow rate is 1 $\mu$L/min) [100].

A critical problem in inkjet printing is related to air-flow oscillations that give rise to print defects due to the misplacement of low Stokes number satellite droplets. This complex problem was investigated using an innovative dispersed-phase continuum method, which permits the force exerted by the multitude of high Stokes number main droplets to be modeled as a continuous smooth field [162]. Results suggested that the oscillations can be linked to the deformation of the primary vortex upstream in the printing zone and consequently the introduction of extra flow in the direction of the platform motion which improves printing quality.

In addition to the process-level DTs, machine-level DTs for material extrusion 3D printers have also been developed and tested for process monitoring and quality assessment [47,256]. For example, Fig. 33 shows the machine-level DT of an extrusion printer which consists of three main modules: a core containing the simulation engine, a data interface managing incoming data, and a graphical interface enabling user remote control.

### 4.3. Laser machining

DT has been explored in several laser machining cases. A self-aware digital twin (Fig. 34) of laser cutting has been developed to reason about behaviors of laser power, machine power, and gas flow, and control the process upon needs [225]. The “self-awareness” was realized by a supervised ML model driven by big data of multidimensionality to reason the process behavior.

Molecular dynamics (MD) simulations were utilized as a DT of femtosecond laser material removal processes by integrating simulation predictions into the DT using ML, process physics, and decision-making algorithms [222].

At the machine level, a DT of the five-axis laser drilling machine tool has been developed by estimating nonlinear multivariable

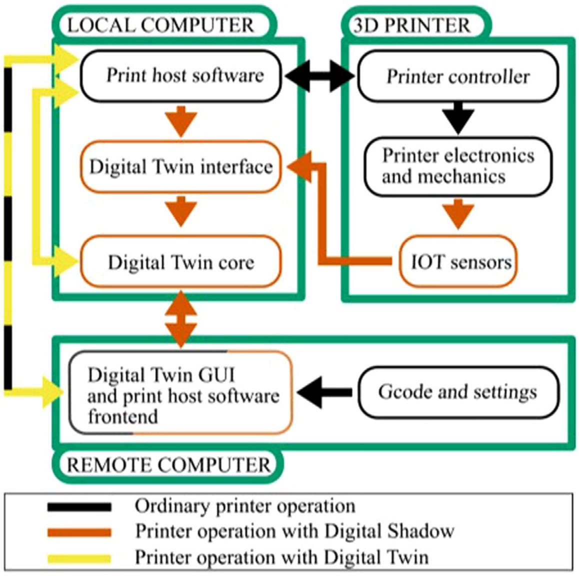


**Fig. 33.** DT structure of material extrusion 3D printers [47].

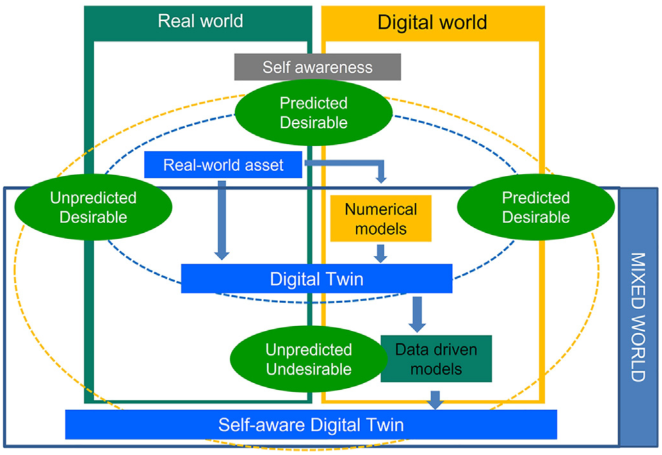


**Fig. 34.** Self-aware Digital Twin [225].

dynamic models in a non-intrusive way using the in-process CNC data [238].

### 4.4. Synopsis of DTs for photonic processes

The literature survey and analysis demonstrate that the maturity of DT models varies from process to process, while L-PBF is most investigated compared to other photonic processes. The bulk is at the stage of the process modeling (i.e., DT) development while the real-time data feeding to a DT and the DT prediction-based proactive process control are still at the conceptual level. From the viewpoint of technology readiness level (TRL), the key components of DT models for AM and laser machining vary significantly: online sensing (TRL 3–7); data transmission (TRL 3–4), process modeling (TRL 3–6), decision-making (TRL 3–5), and real-time control (TRL 2–3).

## 5. Digital twins for electro-physical and chemical processes

In the context of the DT concept for enhancing manufacturing processes, several challenges and opportunities can be identified for the electro-physical and chemical processes. For EDM processes, generally, the process performance in terms of achievable material removal rate (MRR) and sufficient surface integrity – while keeping sufficient process stability – plays a major role in process optimization. For ECM processes, the precise forecast of the resulting workpiece geometry and the derivation of the tool geometry are the most important aspects to be considered. Surface integrity is important as well in ECM, but currently only plays a minor role compared to the macro geometrical aspects.

In contrast to conventional machining processes, e.g., milling and grinding, EDM is already a feedback-controlled process more or less since the very beginning. Nevertheless, there is still further optimization potential in form of DT for the advanced model predictive control loop (two-way data flow between the physical and digital objects). Sections 2.2 and 3.1 can be implemented to still improve process performance based on the actual specific boundary conditions and process characteristics. Regarding the resulting workpiece surface integrity (physical asset viewpoint of DT, Section 2.3), it is of great importance to develop a so-called overall thermal load model to track the relevant local heat dissipation and resulting surface modifications over several process steps. This especially plays an important role for EDM processes as typically several discharge regimes are applied sequentially to reduce the discharge energy and therefore the extent of the heat affected zone (HAZ). The corresponding process chains incorporate roughing and finishing steps for Sinking EDM as well as rough/main cuts and subsequent trim/finish cuts for Wire EDM. Besides the effects on the workpiece, this is also important for the tool to track the wear behavior and therefore resulting in geometrical deviations during its applications.

For ECM technology, the availability of advanced multi-physics simulation approaches in combination with high-performance computing hardware allows nowadays to achieve very precise process forecasts for the achievable workpiece geometry in the digital world. Overcoming the fact of just being a sophisticated process model, actual boundary conditions of a given ECM operation in real production must be taken into account in future DT concepts. Ideally, the actual specific MRR and/or frontal gap size could be determined at an early process phase, which allows for virtually optimizing the process in the meantime. Finally, the optimized machining parameters could be used during the finishing phase in the physical domain – closing the loop of the two-way data flow of the DT according to Section 3.1. In addition, the first models for ECM are available to forecast the local resulting micro geometry. In fact, surface integrity aspects in terms of local phase concentration changes, pitting corrosion, or flow grooves are recently getting more into focus from the part functionality point of view. The related digital replicas cover the physical asset point of view of DT according to Section 2.3.

In the following sections, the current states of process models and transformation levels in the context of the DT concept will be presented and discussed in detail according to the above-described functionality for both EDM and ECM.

## 5.1. EDM

Similar to Metal AM (see Section 4.1), EDM processes involve local steep temperature gradients for heating and cooling of the material and finally also intrinsic cyclic heat treatment due to consecutive process events. Of course, the process itself is intended to subtract material by mainly melting and evaporation instead of adding. Therefore, process models (elsewhere discussed in detail, e.g. [89]) are needed as the basis for any DT approach. But in contrast to AM processes, an additional major challenge can be identified. For EDM, the discharge locations cannot be determined exactly in advance but are the result of a combination of probabilistic and deterministic effects [89]. Any envisaged further DT-based process optimization is therefore highly dependent on a sophisticated digital model describing the actual real-time discharge distribution on the physical object for a given process setting.

To build an overall thermal load model of the workpiece (from the viewpoint of the physical asset) and also of the tool electrode with resulting surface modifications, it is necessary, to track and evaluate the locally dissipated discharge energies in Fig. 35 [252,253].

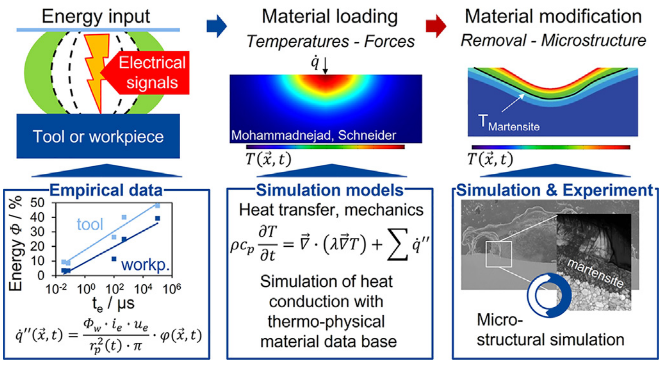


**Fig. 35.** Modeling of energy dissipation of single EDM discharge and simulation of subsequent local workpiece material loadings and resulting modifications (so-called process signature principle) [91]. The DT of the workpiece (physical asset) is built based on the DS of actual energy input.

This can either be done by a kind of white box approach (Section 3.2) analyzing every single discharge over time and position or by a kind of black box approach by incorporating, e.g., statistical approaches, Fig. 36, or worst-case scenario techniques. Also combinations, of course, are imaginable (gray box approaches).

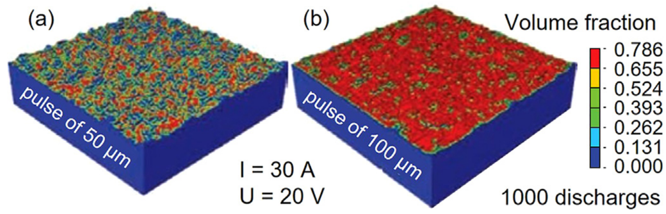


**Fig. 36.** DT statistically describes the martensite evolution of the HAZ as the function of varying EDM discharge durations (a) 50 $\mu$s; (b) 100 $\mu$s for simulated randomly distributed pulses, based on [151].

While first only being a DS of the process as a kind of heat map of the corresponding discharge position and/or local energy distribution, the DS will immediately transform into a DT when additional ICME/ICM$^2$E (Integrated Computational Materials and Manufacturing Engineering) algorithms are incorporated to forecast the material reaction/modification based on the measured process load [245].

### 5.1.1. Tracking of discharge location as a basis for DT

For the detailed tracking of each EDM discharge, it is first important to analyze the exact 3-dimensional coordinates of the plasma channel foot points both on the workpiece and the tool electrode side (if in focus). In the second step, the discharge must be analyzed regarding its locally converted and dissipated heat energy. It must be evaluated which fraction is dissipated into the tool electrode, the dielectric, and the workpiece [253].

To track the exact discharge position, the first attempts were done for Wire EDM as two of the three coordinate components can easily be derived from the machine tool axis positions according to the given cutting path within the G-code, Fig. 37. For roughing conditions, the discharge position is then assumed to be in the frontal position of the wire electrode while for the trim cuts a lateral position is typically assumed. By correlating the electrical process signals with local metallurgical rim zone analysis, first position-based process models could therefore be created to, at least, identify critical areas along the Wire EDM cutting path.

The concept of determining the vertical discharge position over the workpiece height by calculating the ratio of the resulting local discharge currents over upper and lower wire guidance systems has been known for decades [83,141,217]. In the context of advanced process control, this is nowadays successfully used in industrial praxis due to the availability of hardware and computing power on machine tools. Exemplarily, the so-called Discharge Tracker of the company GF Machining Solutions (GFMS) is mentioned which

Please cite this article as: Y. Guo et al., Digital twins for electro-physical, chemical, and photonic processes, CIRP Annals - Manufacturing Technology (2023), https://doi.org/10.1016/j.cirp.2023.05.007

ARTICLE IN PRESS


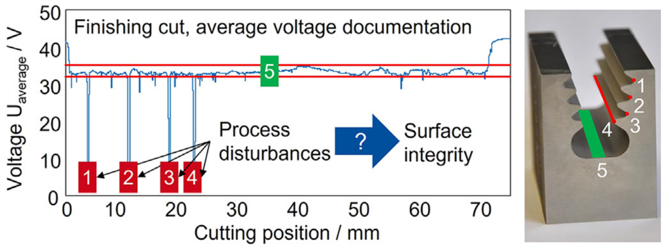


**Fig. 37.** Measured mean gap voltage of manipulated fir tree slot production (a) and location of instabilities (b), based on [91,119].

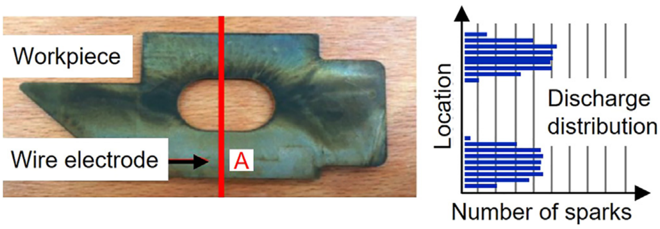


**Fig. 38.** Real-time control of process parameters in Wire EDM based on discharge location measurement, adopted from [28,29].

successfully applies this technology for a real-time process monitoring of each Wire EDM discharge and corresponding process adaptations for changing workpiece heights, Fig. 38.

Concepts for similar determination approaches for Sinking EDM are also known. The basic idea is to measure the resulting individual discharge currents via three or more defined workpiece clamping positions – ideally the four edges for a cuboid geometry [126,135,257]. Based on the given ratios for the two lateral coordinate axes, the lateral discharge position could be reasonably calculated. Taking the frontal tool electrode movement into account, the third coordinate for the discharge position in a workpiece coordinate system can also be derived from a model-based assumption of the frontal gap. While such a measurement system can easily be applied in a lab environment, the industrial application for different and ever-changing workpiece geometries (e.g., tool and die-making industry) turns out to be much more complicated. Nevertheless, concepts for separated tool electrode features with individual discharge current contacts in one universal clamping system have already been presented as prototypes, e.g., Fig 39. This allows, for example, to individually control, adapt, and optimize the discharge currents and the generator usage for different local boundary conditions (e.g., filigree vs. volumetric feature) during Sinking EDM.

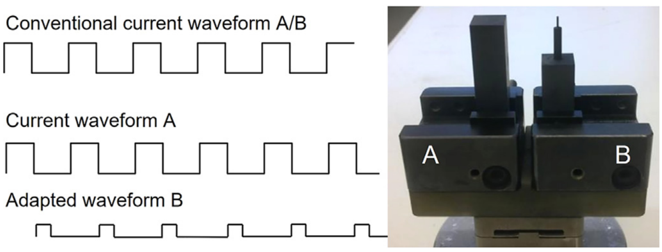


**Fig. 39.** Simultaneous Sinking EDM of different areas with separated tool electrode parts and individual generator connection, based on [27].

### 5.1.2. DT implementations based on the discharge location

GFMS recently presented the first successful industrial application of discharge position tracking during Wire EDM in the sense of a DT for the tool electrode. The wire temperature is calculated in real-time by taking the local model-based thermal loads of normal discharges and the analytical heat conduction into account, Fig. 40. The basic idea behind this can scientifically be traced back to earlier theoretical/static approaches [99,137]. The new approach could be referred to as the physical asset viewpoint – virtually tracking the tool wear based on DS measurements of the locally dissipated energy. Furthermore, this allows for critical monitoring of unfavorable discharge agglomerations which could result in local wire degradations and finally unwanted wire ruptures to be avoided by the advanced process control. The latter case closes the data flow back from the digital object to the physical object satisfying the DT definition.

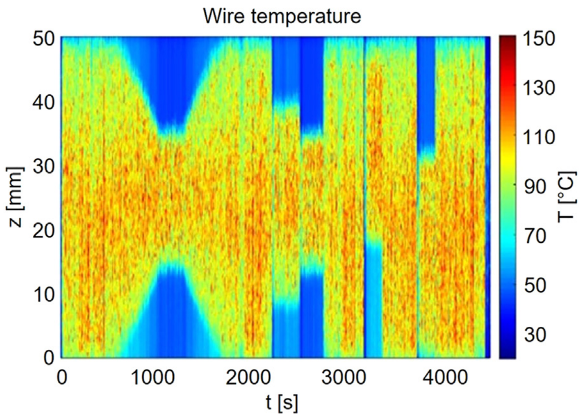


**Fig. 40.** Real-time wire temperature simulation in the sense of DT during the rough cutting of a non-homogeneous height steel part, based on [55].

### 5.1.3. Process sensing as the basis for the DT concept

In the context of process position analysis for Sinking EDM, a systematic correlation between discharge voltage and local discharge position for comparably long and filigree tool electrodes has experimentally been determined, Fig. 41. By setting the corresponding threshold values, the machine process control can therefore determine between frontal and side gap discharge positions finally allowing to suppress unwanted discharges before piloting the high-power level. Therefore, lateral tool electrode wear can be drastically minimized, and process efficiency considerably increases.

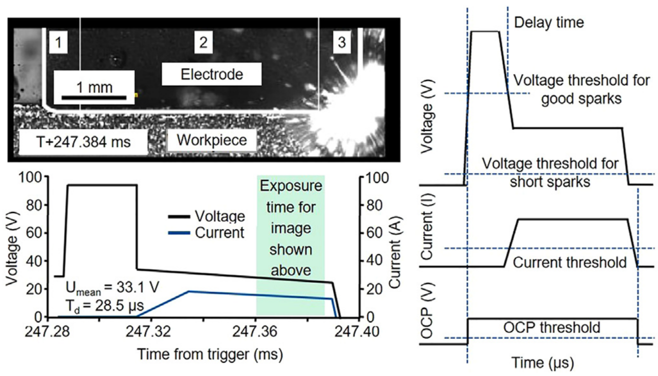


**Fig. 41.** Correlation of electrical signals and high-speed camera images during Sinking EDM: Left: the image of a spark (75 $\mu$s duration, 20 A) and its voltage and current signals, sorted from the acquired oscilloscope data using MATLAB sub-routines. Right: method of spark characterization based on voltage and current thresholds, based on [166].

For an in-process characterization of the energy fraction dissipating into the tool electrode during Sinking EDM, a correlation between the peak acoustic emission (AE) signal and discharge force was experimentally determined for single discharges, Fig. 42. The discharge force acting on the workpiece strongly depends on the local dielectric fluid conditions. High forces can be correlated to discharges in liquid while low forces belong to discharges in the already existing local gas bubbles. Accordingly, the energy dissipation into the electrodes and the dielectric fluid can be modeled specifically and individually. The AE signal might therefore be used in the future as a real-time indicator for the local discharge conditions and the resulting energy dissipation, resulting in individual thermal loads for a single discharge. This

Please cite this article as: Y. Guo et al., Digital twins for electro-physical, chemical, and photonic processes, CIRP Annals - Manufacturing Technology (2023), https://doi.org/10.1016/j.cirp.2023.05.007

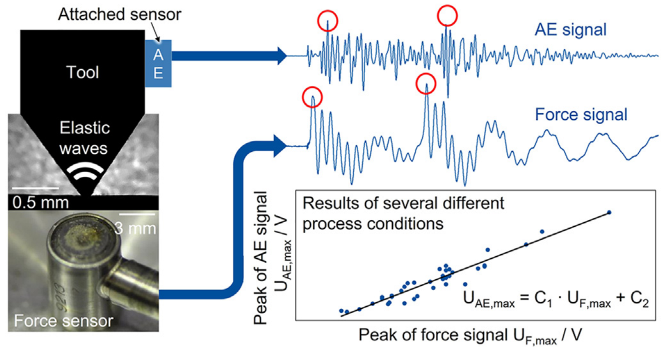


**Fig. 42.** Information about discharge forces contained in the AE signals as a further process sensing approach as a basis for DT, based on [91].

could then also be done for a sequence of consecutive discharges, see [91,111].

### 5.1.4. Basic adaptive control and data-driven approaches for DT

Besides the just-described white box modeling methods, black box (i.e., data-driven) modeling approaches also exist for EDM. These also serve as the contextual basis for future DT concepts. They include – typically based on the application of AI – early Adaptive Control Systems, Fuzzy Logic up to Virtual Operators, and the latest advanced Neural Networks (NNs) [211]. Adaptive Control Constraint (ACC) and Adaptive Control Optimization (ACO) have been applied to EDM die-sinking applications, e.g., [88,219]. These were foreseen to improve the machining results – either reaching a target or a maximum value – by altering the established standard machine control based on process background knowledge and prior machining results. In the same context, expert systems (ES), aka Knowledge-Based Systems (KBS), were established especially focusing on the automated feedback of expert user experience to improve the process, see e.g., [220].

Around 1990 the application of Artificial Neuronal Networks (ANN) approaches was established in EDM for further data-based process optimization. Typically, MRR and surface roughness (Ra) could be modeled much faster and more accurately for the given boundary conditions mitigating the challenges of high complexity and stochastic nature of the EDM process, e.g., [97]. In parallel, also purely statistical-based approaches – particularly the Analysis of Variance (ANOVA) became very popular for EDM modeling. Up to now, many papers have been published in this context so far. While on the one hand representing pragmatic and efficient modeling approaches for EDM processes, the broad applicability, and generalization capability as well as a better scientific process understanding are on the other hand very limited (i.e., only gaining trivial results that, e.g., the discharge current has the highest influence on the MRR). Only a very focused and heuristic setting can finally be covered by these basic modeling approaches. For serial and mass production scenarios this could give added value to the industry, but by far most EDM applications only represent single-piece production with ever-changing boundary conditions.

In the mid ninetieth year, the Fuzzy Logic (FL) application for optimizing the gap control of EDM was introduced in machining systems, e.g., [31]. FL allowed the implementation of qualitative and nonquantitative rules – close to human expert reasoning – for describing highly non-linear process behaviors. Therefore, a wider range of operating conditions could be covered compared to conventional controllers. In addition, also Neuro-Fuzzy approaches – combining FL with ANN – were developed, e.g., [15,118]. Finally, the Genetic Algorithm (GA) and recently the Evolution Strategy (ES) were introduced to EDM modeling approaches to take randomized input parameters into account. The ES, which is a stochastic metaheuristic optimization method, allows for efficiently optimizing EDM drilling parameters, see [227]. Again, GA and ES modeling approaches are only valid under limited process conditions (chosen material, tool, dedicated geometry) and do not allow a generalization of the results.

Stochastic optimization algorithms have also recently been successfully applied to the optimization of EDM drilling operations, [165]. Hierarchical cluster analysis has been used for pattern recognition during Sinking EDM process monitoring. The method allows the identification of a set of suitable and non-suitable machining conditions through a variety of key process parameters. The key advantage of the unsupervised approach is that the analysis can be performed by observing all the relevant sensor features simultaneously [39,40]. Also, big data analytics is nowadays researched in EDM series and mass production of fuel injection systems which provides a data basis for DT [122].

### 5.1.5. Emerging data-driven concepts representing the DT concept

Selected emerging and outstanding examples of data-driven concepts – with high significance for the development of the DT idea – will be presented in the following:

An industrial important recent approach includes the image-based measurement of workpiece roughness using ML techniques during Sinking EDM, Fig. 43. By integrating an inexpensive industrial camera system into the machine tool, fast closed-loop control of the surface roughness is nowadays achievable allowing an in-situ and automated metrology step without the need for demounting and unclamping of the workpiece. The approach relies on a Convolutional Neural Network (CNN) analysis of the Ra value which must first be trained by experiments for a given workpiece and tool electrode material and according to process settings (heuristic frame), see [69,206].

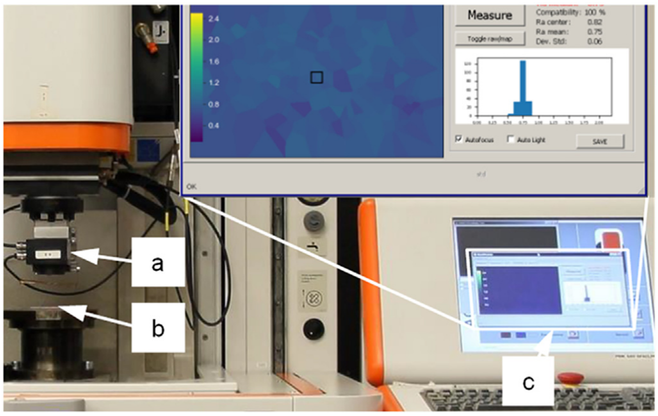


**Fig. 43.** Sinking EDM machine with imaging sensor (a), the workpiece (b), and integrated GUI (c), for AI-based roughness analysis, based on [69].

While on the one hand representing a two-way data flow from physical to digital object and back, a necessity for real-time application on the other hand is not given. In fact, this DT loop must be executed between different process steps and could therefore also fit ideally to the concept of the product/physical asset-driven DT.

Another promising approach includes the model-based determination of unwanted discharge characteristics during Sinking EDM. By taking a worst-case scenario into account for a probabilistic discharge distribution along the height of a filigree tool electrode, Fig. 44, unwanted heating, bending, and final rupture as a function of the discharge settings can be forecasted and avoided by advanced control loops. This approach allows a fast Monte Carlo simulation of discharge position scenarios and is therefore efficiently avoiding the need for overall discharge monitoring, see [91,265].

Further work focused on a simulation method of Sinking EDM by determining discharge locations based on spots with the shortest discharge delay time. The simulations repeat their routines consisting of the determination of discharge location, removal of electrodes, generation, and displacement of debris, and tool electrode feeding. The

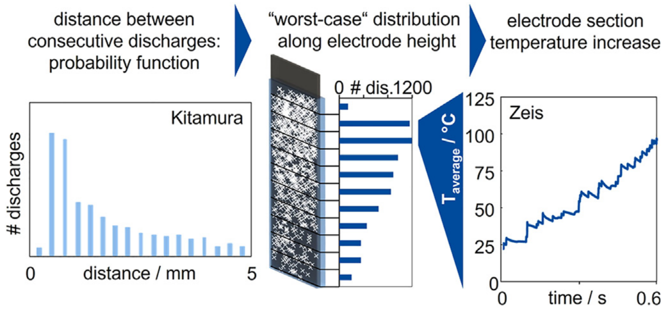


**Fig. 44.** Determination of unwanted discharge distributions in Sinking EDM by an iterative approach to defining characteristic curves (data source left side: [108]), based on [91,265].

calculations are done probabilistically assuming that an exponential distribution applies. Simulation results were in good agreement with the experimental data for different working surfaces [180].

The studies for reciprocated traveling Wire EDM proposed a method of online estimation pf the workpiece height based on a support vector machine (SVM). The algorithm was integrated into a newly developed CNC system to monitor current and voltage signals from the discharge gap and an adaptive control unit. Training data were derived from machining stair-shaped workpieces and validation was finally executed by machining variable heights. The overall machining time was reduced by more than 30% and the resulting estimation error was within 2 mm [94].

For the "zero-defect" manufacturing, an advanced process monitoring procedure was designed and tested for detecting process conditions which lead to surface defects in Wire EDM. Based on signal feature extraction for the construction of sensor fusion pattern vectors, a methodology has been proposed and implemented with a high sampling rate of 100 MHz. The extracted features from the experimental data were used to construct the pattern vectors to be used as input to the supervised NN algorithm to find correlations between signal features and surface quality. Results showed that a strong correlation exists, as the success rate was always above 80% [41,42].

Research work on pattern recognition during Wire-EDM focused on the time-based analysis of process stability by analyzing the discharge energy. Differences between characteristic parameters of a stable and unstable process and the distribution of different discharge types have been investigated, which provides a basis for early detection of process anomalies, e.g., wire breakages [23].

### 5.1.6. Recent data-driven approaches toward the DT concept

A further logic development in Sinking EDM targets not only suppressing unfavorable discharges but also actively adapting the ignition voltage, Fig. 45, in real-time for every single discharge realizing a sort of electronic servo system [32]. This SPVC (Single Pulse Voltage Control) could react 1000 times faster than the established mechanical servo system. A prototype system shows remarkable increases in the discharge frequency and consequently in MRR without penalizing the other process characteristics.

Another recent approach comprises the development of virtual operators in EDM with self and transfers learning ability, Fig. 46. Inspired by the typically great experimental knowledge of experienced human operators in EDM, an automated machine system is created by incorporating Bayesian Optimization with Gaussian-distributed processes for multi-dimensional model-based process optimization based on experimentally gathered process information of dedicated case studies [57].

Real-time sensing approaches for Wire EDM applications have been analyzed by applying FPGA (Field Programmable Gate Array) tools during online process monitoring to constantly detect and evaluate single discharges with high measurement frequency. The system finally only stores characteristic numbers and thus a continuous

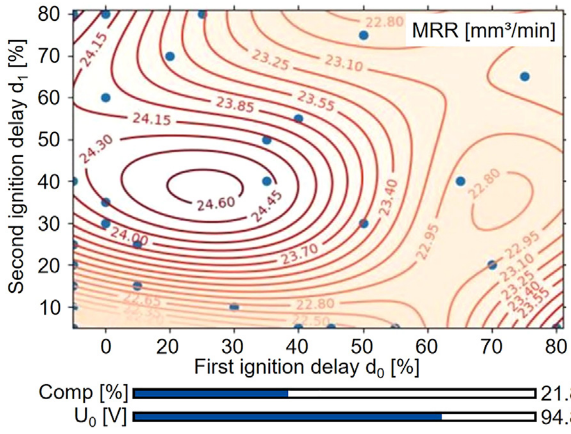


**Fig. 45.** AI-based derivation of a digital representation of MRR for Sinking EDM. Based on this DS, process optimization in the sense of DT can be achieved, d0 and d1 can influence the single discharge form, based on [32].

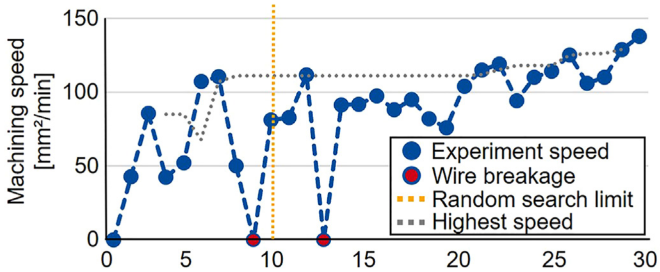


**Fig. 46.** Bayesian Optimization of machining speed for Wire EDM as a basis for efficient DT transfer learning process optimization, based on [57].

process can be recorded without generating too large data volumes [139].

With the help of FPGA technology, the discharge location tracker (DLT) of GFMS could be enhanced for an industrially implemented ISPS (Intelligent Spark Protection System). This system monitors and avoids local discharge concentrations and is, therefore, able to increase the general level of applied energy. Even with the increased pulse energy, the resulting white layer still could be kept similar because of the realization of a homogeneous discharge distribution. Finally, the usage of DLT as a measuring device of the height curvature is envisaged [30].

Recent advances in Wire EDM, therefore, comprise the prediction of geometrical accuracy by analyzing continuously recorded process data. Here, it is important to take the effect not only of normal discharges but also of short circuits into account. Fig. 47 exemplarily shows the spatially resolved ratio of normal discharges over the workpiece height. Locally, this ratio can be reduced but the introduced energy is increased [138].

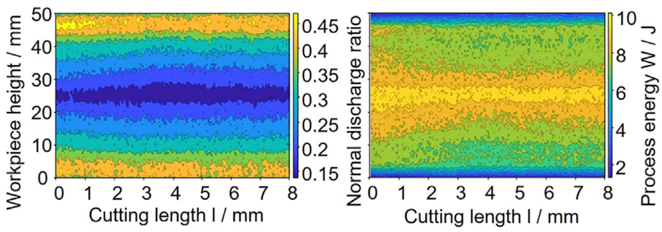


**Fig. 47.** Heat maps of the ratio of normal discharges and disseminated process energy over workpiece height and cutting length, based on [138].

Taking the significant effect of short circuits into account, unsupervised ML was further applied to ensure that no relevant information is lost. As a result, the determined statistical variables, e.g., Fig. 48, show a good correlation with the experimentally determined workpiece curvature. A model could, therefore, be developed in the

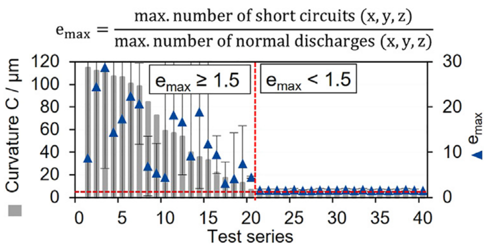


**Fig. 48.** Correlation between wire EDM workpiece height curvature and the ratio of the max. # of short circuits and normal discharges, based on [140].

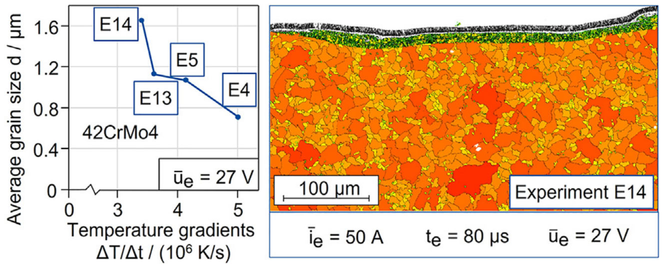


**Fig. 49.** DT-based modeling of the grain size distribution of the workpiece by phase-field approach as a function of varying discharge conditions, average grain size concerning temperature gradients (a), EBSD of crater cross-section for experiment number 14 for validation (b), based on [22].

future in the sense of DT that predicts the geometrical accuracy based on process data only [140].

Further research work focuses on the data-driven statistical analysis of the discharge positions of consecutive discharges along the wire length and the workpiece height as a function of the discharge frequency. Resulting probability distributions should be used in the future to predict the next discharge positions and suppress unfavorable events in advanced process control [131].

### 5.1.7. DT concept as a virtual replica of the product

For achieving maximum output out of the DT concept, it is necessary to change the product (i.e., physical asset) point of view. Ideally, the existing process models can here be taken as the basic transfer function to build an in-process/real-time DT of the workpiece, the tool, and the machine tool. This virtual twin of the real physical object is then always available to track the current status. By applying physical modeling a DT is formed out of occasionally derived DS information used for alignment and validation. Therefore, intermediate processing or usage steps along the process chain – without the chance to apply measurements – can be interpolated and future behavior even up to the use phase extrapolated. Some (further) examples and ongoing research work will be presented as follows.

Recent work regarding the discharge energy-dependent material load on the workpiece side (in the frame of the Process Signature Concept, see Section 2.3) calculates in detail the up-to-now unknown and not measurable temperature field induced during single discharges as well as during consecutive discharges [209]. While the heat dissipation of the single discharge is described according to the given heat conduction equation, the heat load of consecutive discharges uses probability models to derive the according distances on the workpiece surface. Also based on the physics-based calculation of the workpiece thermal load of single discharges, a phenomenological correlation to the resulting residual stresses for the continuous process becomes possible. A model-based prediction of the stress distribution as a function of discharge energy and workpiece material (including heat treatment state) under the given experimental boundary conditions could successfully be shown for EDM processes, see [112]. Even complete physics-based modeling is currently aspired, [210]. A first example in the micro domain successfully compared calculated and measured deformations [260].

A high-fidelity simulation method was developed for Wire EDM by solving the reverse process problem using parametric programming. Parameters, including the ignition delay time, explosive force, damping coefficient, and relative permittivity of dielectric are difficult to measure in actual machining conditions and are, therefore, determined to solve the reverse problem. The simulation process includes searching for discharge locations, removing material, and analyzing wire vibration [84].

As first modeling approaches for the resulting surface modification of EDM generally assumed a total transformation to martensite, see [151,152], the latest modeling approaches based on the phase-field approach simulate in detail the micro structure evolution, e.g. Fig. 49, as a function of the thermal cycle (heating and cooling gradients) and the given local material micro structure, [21,22]. This procedure can be interpreted as DT as the DS of the locally dissipated discharge energies is further digitally processed to forecast the resulting surface modifications. By consecutively executing this modeling procedure, a complete EDM sequence and even process chain could be virtually replicated in a DT representing the aspired overall thermal workpiece model.

Physical asset approaches incorporate the virtual tool electrode feed path planning for multi-axis EDM. The goal is to plan an interference-free and optimal tool movement while keeping the size of the electrode as large as possible for complex workpiece geometries during a dynamic programming methodology [153,154]. Further approaches focus on the reverse simulation of suitable tool electrode geometries for complex target workpiece geometries taking the wear behavior into account. The experimental results showed that the EDMed workpiece geometry was closer to that of the target workpiece when the tool electrode shape was obtained from the reverse simulation compared to offsetting the target workpiece shape at a distance equal to the gap width [134,136].

Considering the wire electrode as a physical asset, an in-process modeling of wire displacement was successfully developed based on 2D optical wire displacement measurement above the machining area and an inverse simulation of the discharge reaction force. Therefore, virtually the 3D wire behavior could be predicted in the context of a DT approach [215]. Even the discharge location could also be taken into account with the chance to update in real-time during machining [216]. Again taking the wire electrode into focus, CFD analyzes and simulates the influence of nozzle jet flushing near steps in the workpiece heights [107]. This is of high practical importance for the avoidance of wire breakages before the actual step position during machining is reached which could be determined by a corresponding DT of the wire in the future.

### 5.1.8. Synopsis of DTs for EDM processes

The successful development and application of the DT concept in the EDM area still need further steps going far beyond the actual state described as being in its infancy. Most important is the aspect that for a reasonable and industrial-relevant implementation the concept must especially overcome only applying process models and/or simple workpiece material models. In fact, the actual boundary conditions of a given machining operation in real production must be taken into account. This applies, for example, to the integration of the real workpiece conditions in form of the current material characteristics as well as the influence of actual given geometrical influences. On the TRL scale, most current DT approaches and ideas can be classified as levels 2–3. Only the spark location-based wire temperature measurement and the AI-based surface characterization loop could be labeled levels 4–6.

## 5.2. ECM

To generate a fully digital model to forecast both the macro and micro geometrical evolution of the workpiece geometry for ECM, multi-physics FEM simulation approaches have been established during the last 10–15 years [120,121]. These models allow comprehensively taking all thermal, electrical, chemical, and fluid-dynamical aspects into account in modeling material removal to precisely describe the changing electrolyte properties along its flow path, see Fig. 50. The time-based evolution of the

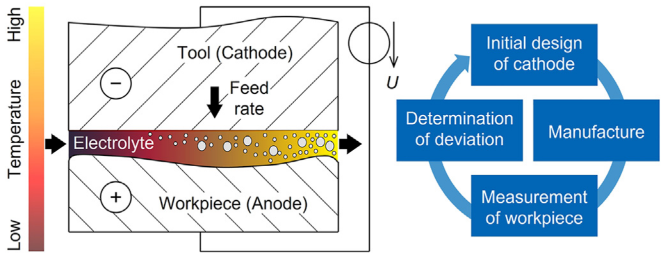


**Fig. 50.** Fluid characteristic-dependent material removal during ECM and resulting iteration cycle for process design, based on [116,120].

workpiece geometry can therefore be virtually displayed for a given tool electrode geometry and process setting. This allows for the drastic reduction of experimental efforts in the classically established process design iteration cycles, see Fig. 50. In an inverse approach, this digital process model can also be used to optimize the tool electrode geometry by correcting digitally final deviations. Thus, the extensive and inefficient efforts of experimental iterations to optimize the overall material removal process can be drastically minimized with this new virtual approach [121].

### 5.2.1. Multi-physics process models as the basis for DTs

The most important aspect of all modeling approaches is the correct local and overall physical description of the fluid characteristics in the complete tooling system. Local fluid velocity and resulting gas volume fraction due to electrochemical reactions have a strong influence on the resulting local fluid temperature increase by Joule heating, see Fig. 51. Therefore, the resulting spatial conductance can be increased in a self-reinforcing cycle. These effects, which could result in local form deviations, can only be identified in the digital approach as real production only can take place in a completely closed setup. This strongly applies for constant Direct Current applications (DC-ECM) – typically used for roughing operations – or jet applications (Jet-ECM) – but also for electrically pulsed (Pulse-ECM) as well as additionally mechanically pulsed/precise (PECM) variants – typically used for precision and finishing applications, [116,117].

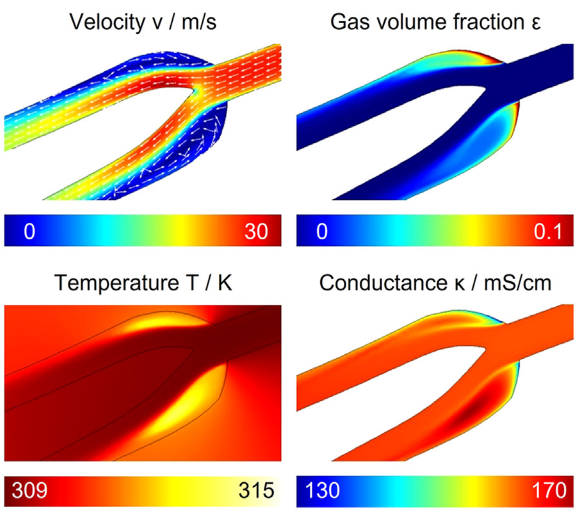


**Fig. 51.** Digital model of fluid characteristically phenomena at a blade trailing edge towards the end of DC-ECM as a basis for DT, based on [121].

In the context of virtually impossible experimental accessibility, the idea of virtual sensors gains high importance to locally analyze the exact process conditions, e.g., PECM [114] and Jet-ECM [207]. Hereby, insufficient fluid flow, boiling of electrolytes, or cavitation phenomena [110] can, for example, be identified. This especially becomes true for PECM processes where much higher transient gradients and amplitudes of process quantities are addressed compared to the relatively stationary DC-ECM [115].

Due to the high demand for computation power and robust mesh deformation algorithm, a transient multi-physics simulation of complex 3D geometries is not economically feasible. A feasible approach to a practical simulation would be another consideration of different physical phenomena as well as the constriction to static simulations [20]. In addition, multi-scale [208], order reduction [159], or shortcut methods [19] have been proposed to tackle the time-based dimensional challenges in PECM simulations.

Successful applications of multi-physics modeling approaches can exemplarily be seen for the simulation-based cathode design for Pulse-ECM jet engine vanes production [59], PECM impeller manufacture [157], and precision machining of internal macro geometries (i.e., involute splines or feather key grooves) [79]. Also, cooling hole precision during DC-ECM sinking could be evaluated by analyzing the electrolyte temperature field [149]. An efficient roughing of BLISK (Blade Integrated Disks) channels by DC-ECM with variable feed rates could be designed based on modeling approaches [240]. Areal PECM machining of metallic interconnect plates with a flow channel array for fuel cells could be optimized by the application of multiphysics simulation approaches to enhance flushing performance [155]. Similar investigations could support the optimization of internal flushing arrays in AM-manufactured tool cathodes [86]. Also, simulation-based process design for Jet-ECM took place [80].

### 5.2.2. Digital object representation approach for physical assets

Besides focusing on the development of advanced process models as the basis for DT, the digital replica (i.e., DT in the sense of a physical asset) of a physical object is very advantageous for optimizing ECM processes. The effect of process parameters can for example be evaluated on the DT of the workpiece in a virtual iteration cycle parallel – or in the future before – applying it to the real process. An example of a turbine blade manufactured by PECM and simulated in parallel is given in Fig. 52. Simulated current density and measured form deviations of the real process correlate quite well, which validates the applicability of this approach.

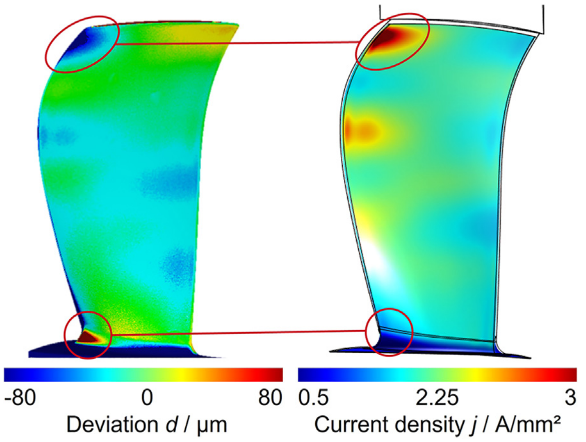


**Fig. 52.** Physical object (turbine blade) and digital representation (DT in physical asset view) represented by form deviation optically measured compared to nominal geometry and current density acting on the part for PECM within a simplified stationary 3D simulation, based on [20].

In the context of intersecting line removals during Jet-ECM, multiphysics simulation approaches have also been developed to analyze asymmetrical temporal removal behavior and to derive potential for optimization [190]. Based on this, a finite element area grit-based simulation of jet electrochemical material removal on the workpiece side was developed [247]. This new approach is less resource-intensive and complex compared to the established FEM or Finite Volume Method (FVM) [246]. In the underlying model, the surface of the workpiece is divided into square sections. To each of the squares, a time-dependent depth value in the sense of a DS/DT can be assigned to track the topography evolution. Point as well as line removals and even crossing lines could successfully be modeled. Finally, a 3D process model has been developed and validated to predict the resulting surface geometry of curved channels and calculate optimized feed rates for locations of the toolpath with impaired geometry [26].

Finally, models regarding the microstructure evolution during ECM have also been developed. This is especially important for the forecast of surface roughness but also surface integrity for multi-phase materials. One example is shown in Fig. 53 where the inhomogeneous pearlite dissolution in a passivating electrolyte system is presented. The decisive impacts of the oxide layer and the electric double layer were studied utilizing a thin semiconductor layer in the model. This allows the different properties of each material phase be taken into account in the example of the steel 42CrMo4 [113]. The microstructural aspects including the description of the change of local phase concentrations and the development of flow grooves during ECM are characterized in [18]. Surface smoothening as a function of process time is furthermore important to gain the whole picture. First modeling approaches can, for example, be found for plasma electrolytic polishing [49]. A stochastic method was set up to predict the achievable surface roughness based on the initial one and after a standard and a jet-based process variant.

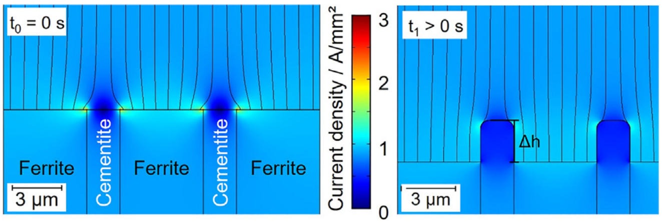


**Fig. 53.** Digital product analysis regarding micro geometry –simulation of inhomogeneous pearlite dissolution during ECM, based on [18].

### 5.2.3. *ECM process sensing as the basis for the DT concept*

Numerical models regarding ECM usually do not describe the dissolution process by including all relevant physical equations in detail. Especially for multi-phase materials, the large number of degrees of freedom requires a suitable modeling approach for describing the effects with sufficient accuracy. Therefore, experimentally derived values typically serve as the basis for multi-physics simulations [103]. The applicability and suitability of the frontal standardized gap experiments for modeling and simulation of lateral gaps were successfully analyzed for the current density distribution. Simulations have to be refined only for applications with uncontrolled electrolyte outlets.

The methodologies to consequently align the simulations with specific experimental data (i.e., measured specific MRRs) in the context of specifically entitled DT approaches were presented for PECM [160] as well as for Jet-ECM [158]. Defined data chains foresee the removal characterization feeding the simulation to derive optimized process parameters for the given machining task.

For the DT development of the workpiece, it is important to know the exact working gap distance over time. This can either be determined during the already mentioned basic material removal trials offline. An alternative – at least for PECM – could be to use the electrical current during the process as in-process sensing of the working gap. By using piloting pulses for different known tool electrode positions, the exact distance could be calculated based on the difference in the electrical currents.

The electrolyte jet of Jet-ECM can be used accordingly for gap distance measurements. This can be done by detecting electrical signals like the actual total current, see [263]. The working gap can therefore be adjusted before and controlled during the process. The surface topography can likewise be measured using the electrolyte jet to determine the electrical parameters when passing over the surface, Fig. 54. Features can therefore be evaluated post-machining using the "dormant" excitation of the electrolyte jet [25]. Following a simple

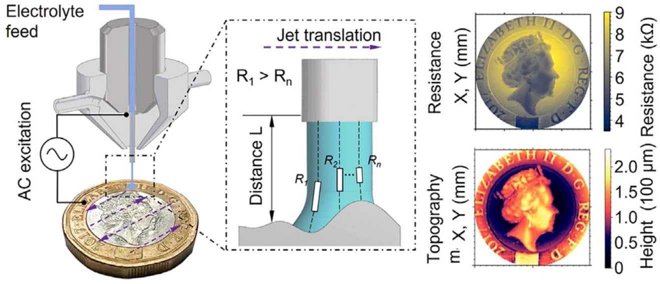


**Fig. 54.** Principal and example of Jet-ECM measurement, based on [24].

calibration of the jet resistance response, high measurement accuracy is achieved.

The proposed technique will enable rapid on-machine inspection of Jet-ECM surfaces leading to better process control. An example comparing the Jet-ECM with a tactile measurement is shown in Fig. 55. The developed measurement system further claims to provide a low-cost but accurate surface imaging approach that can be easily integrated with industrial ECM processes [24]. Consequently, another approach proposes that Jet-ECM can be applied to create depth-controlled measurement surfaces for metallographic analyses at a significantly lower cost and time intervention than electron beam-based analysis methods [221].

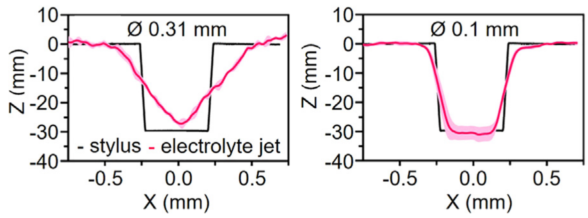


**Fig. 55.** Comparison of stylus and jet measurement of reference groove using different nozzle diameters, based on [25].

### 5.2.4. *Data-driven approaches as DT basis*

Besides physical-based approaches, relevant data-driven approaches can recently be identified for ECM. The industry is nowadays able to track and store high data volumes. Especially for highly complex systems and processes, hidden relationships may be uncovered by data science approaches. Using data mining approaches like clustering, parameters like voltage, current, or fluid conductivity were successfully correlated with optical measurement data during PECM blisk production [266]. Therefore, process anomalies and new approaches for process control could be identified. Further works include the development of online evaluation systems [232]. A further work presents a complete framework for a data-driven ECM model, which is based on the supervised machine learning approach, for predicting the final profile of the machined feature in the ECM process [249]. After training this data-driven neuronal network model, successful predictions and experimental validations have been conducted for laser-electrochemical machining. Parameters even outside the given window have been used to demonstrate the performance of generalization and applicability to a wide range of machining parameters. Lastly, DoE (design of experiment)-based statistical analysis methods have effectively been applied to ECM processes like the Jet-ECM variant [264].

### 5.2.5. *Synopsis of DTs for ECM processes*

The successful development and application of the DT concept for the area of ECM also still needs further development steps. In fact, the process models still need to be enhanced to suit an automated digital replica. While the fundamental governing equations of ECM are already known for a long time [89], the current typical FEM-based multiphysics simulation approaches still represent relatively complex systems only to be operated by experts. Also, computation-intensive tasks like remeshing still need novel approaches to make the simulation approaches more robust and industrially applicable, e.g., [236]. First attempts for more "user-friendly" 3D simulations for ECM were already presented 15 years ago, see [33], but still, a lot of effort is necessary. In the context of IoP (Internet of Production) concept, cloud-based solutions including the rental of both soft- and high-performance hardware (as well as expert support) seem to be a current interesting alternative, and a new business model for optimizing ECM processes with the help of DTs could become possible. On the TRL scale, the current DT approaches for ECM can be classified as levels 1−3.

## 6. Industrial DT trailblazers

Industry leaders have realized the immense potential of DT. A few early adopters have already started frameworks for the product or process design utilizing DT principles [197]. An excerpt from the manufacturing trends 2019 report published by Microsoft has eloquently summarized the value of DT to the industry [174]. Mostly, DTs are used for quality control, improvement, system diagnostics, monitoring, optimization, and prediction of production outcomes and machinery performance [46]. In a 2019 review, recent examples of DT applications were presented in healthcare, aviation, software, transportation, defense, and manufacturing, to name a few [196]. By 2021, 20% of G2000 manufacturers will depend on emerging technologies like IoT, machine learning, and blockchain to automate large-scale processes [174]. DTs empower manufacturers to take corrective actions in nearly real-time. It is estimated that there will be approximately US$36 Billion IoT connected devices by 2021 and IoT is projected to create US$15 Trillion of global GDP by 2030 [174], which hints that companies with IoT-enabled physical assets will be favored strategically and make the most out of this DT revolution.

In Deloitte's 2018 white paper [182], some key signals for the growth of DTs have been elucidated. Market leaders and chief product innovators have already identified DT as an instrumental component to accelerating product design and innovation cycle, process efficiency improvement, and optimization of daily production operations coupled with predictive maintenance capabilities. Not to forget, it is the courtesy of DT that corporations today can plan large-scale infrastructure changes by creating a virtual model of the proposed designs [196]. As part of the digital transformation programs under the Industry 4.0 paradigm, Gartner predicted that "billions of things in the near future" will be represented by their digital avatars, which in itself is a true testament to the huge expectations placed on the exponentially growing technology avatars [182,185].

DT technology continues to get greater acceptance and attention from industry leaders, such as Amazon, General Electric, IBM, Siemens, Microsoft, and ANSYS which are among the top players. Giant technology companies, e.g., GE Digital and Microsoft (with its Azure DTs), are offering commercial DT solutions for different levels of production. NVIDIA Omniverse is the world's first scalable, multi-GPU DT platform. The partnership between NVIDIA and Siemens will integrate NVIDIA Omniverse and Siemens Xcelerator, which enables an industrial metaverse with physics-based digital models from Siemens and real-time AI from NVIDIA in which companies make decisions faster and with increased confidence. In addition, Ansys Twin Builder is an open solution that allows engineers to create simulation-based digital twins with Hybrid Analytics [4].

As DTs continue to top the industry trend charts, it is projected that DTs will be utilized by up to 50% of large industrial companies, which could potentially save billions in operation and maintenance [92]. According to expert reports, up to 60% of manufacturers will be monitoring product performance and quality using DTs and approximately 60% of global companies will use DTs to offer better customer service [179]. Though having a lot of potential, DT projects need to be backed up with a sound business case and greater accountability to ensure full-scale integration from pilot to production environment.

Digitalist magazine [92] outlined six key benefits of DT technology. Specifically, DTs can help companies to: (1) minimize product, asset, and supply chain complexity to maximize quality and performance; (2) gain a holistic perspective to better manage risk and safety; (3) broaden external networks to enhance partner collaboration; (4) create new business models, offer differentiated services, and maintain consistency to compete for both globally and locally; (5) collect real-time data to accelerate and improve decision making; and (6) develop individualized products to deliver superior customer experiences. IoT sensors and data analytics are two key enablers of the potential of DT. IoT sensors help generate a huge amount of data and sound data analytics help draw sensible conclusions about the health of the product and related processes in situ.

## 7. Challenges and outlook

Putting the state-of-the-art analysis in the context of the DT framework, it is clear that DTs face many challenges to achieve the goal of real-time digital models that allow for automatic self-diagnosis, self-optimization, and self-configuration. On the other hand, as an enabling technology for Industry 4.0, DTs also have the unique opportunity to leverage interdisciplinary knowledge. CIRP as a platform makes it a viable technical approach for a broad range of industry and service sectors. The CIRP research community is in a unique position to play a pivotal role in addressing these challenges. The key challenges and potential research directions are discussed as follows.

### *7.1. Federated database management system*

#### *7.1.1. Heterogeneous data curation and integration*

Data is the foundation of DT. Manufacturing processes generate a large volume of heterogeneous/multimodal data from sensors, simulations, machines, and quality characterization. Databases store these data on disk in persistent so that the data can be accessed and reused by the users later. Users can perform in-depth and complex data analysis in the future. Moreover, the user can explore, visualize, and monitor the data stored in databases using well-studied specialized tools. However, database systems are well known for being "one-size-not-fit-all" [226], i.e., no database system can handle all kinds of data. To store the heterogeneous data generated in manufacturing processes, multiple database systems may be leveraged, e.g., an image database to store the melt pool images taken by the CMOS camera and the emissivity images taken by the pyrometer during a metal AM process, a time-series data to store physical features of melt pool such as the spatial and temporal distribution of temperature, pressure, and velocity, a feature database to store the learned features and predictions made by process models, and a regular relational database to store the simulation data, quality data, and CAD data.

To manage these databases, a federated database management system is required to provide a common user interface to store, link, and query the data. Records stored in different database systems can share the same identifiers to link related data. The record identifiers are managed and assigned by the federated database management system. The system also keeps metadata and catalogs of all the data stored in the databases. Users issue queries directly to the system. It converts the query based on the record identifier, metadata, and catalogs to one or more specific queries to the underlying databases and returns the desired data to users.

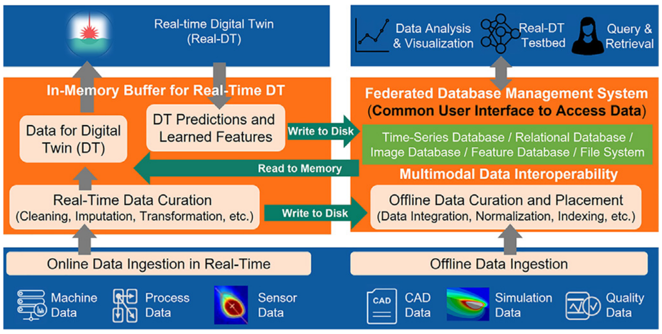


**Fig. 56.** Cyberinfrastructure for real-time DT.

#### 7.1.2. Online and offline data curation

Sensors are prone to fail, and sensed data could be noisy. Spikes, outliers, delays, and missing data are not uncommon in the time-series sensor data. Furthermore, data fed to the process DTs are usually preprocessed to meet the specifications of the models. For this purpose, online and offline data curation is required (Fig. 56). Online data curation leans towards efficiency while offline data curation leans towards data quality.

Online data curation consists of data cleaning, data smoothing, data transformation, and data imputation. Simple models and algorithms are often used for online data curation for efficiency consideration. For delayed and missing data, algorithms and lightweight models can be developed to impute the data. For spikes and outliers, approaches to smooth the data may be designed while maintaining the trends as much as possible. In addition, efficient data wrangling to transform the data from one format to another remains to be studied.

Offline data curation consists of data integration, data standardization, and indexing. Programming-by-example (a.k.a. program synthesis) techniques are required to automatically generate scripts/codes/programs to standardize data. The system may take a few user-provided input-output examples as input, produce some programs that are consistent with these examples, and rank these programs. This process could be repeated until the user is satisfied with the generated program. Data integration and standardization are the keys to ensuring data interoperability. With data integration, potentially related datasets could be found and linked together in the context of a concerned process. For this purpose, content similarity, semantic similarity, and uniform record identifiers can be leveraged to link related data. In addition, data indexing will be useful for fast query access.

### 7.2. Real-time data updating to the DTs

IoT sensors enable continuous process monitoring, resulting in data-rich environments, but meanwhile, necessitate the regularization of data acquisition in terms of both quality and quantity. The process data may evolve and show occasional, unexpected changes. To make the DT framework adaptive and robust to these adversarial factors and continuously deliver expected process outcomes, real-time data updating must be incorporated into the process DTs, ML models in particular, that underly the DT framework. Not only does this updating procedure control production indices but it also facilitates dynamic optimization [178].

The sensor data, image data, and process data are generated in real-time at high velocity, while the CAD data, simulation data, and quality data can be produced offline (Fig. 56). For a process DT, it is key to process the high-velocity data efficiently and feed them directly to the process DT. An in-memory buffer needs to be managed. The process DT can take data in the in-memory buffer as inputs directly.

Data generated offline can also be sent to the federated database management system for persistent storage. Data generated online go to the in-memory buffer to be processed in real-time and fed to a real-time process DT. The data in the buffer needs to be first curated such that its format and quality meet the requirement and specifications of process DTs. At the same time, a copy of the data can be periodically written to disk through the federated database management system for persistent storage. The memory occupied by the data written to the disk can be released anytime to make space for the buffer. The buffer replacement could be managed by the system algorithmically to make sure no data is lost while maintaining high throughputs. In addition, the in-memory buffer may read some data from the databases necessary to process DTs, while predictions and decisions made by the DTs are written to the federated system to be reused and analyzed in the future.

With the data stored inside the in-memory buffer, an established ML model can be updated and adapted to the new environment or evolved process. For conventional ML, model updating requires retraining with new data, which creates a certain lag in time and is computationally expensive. Recent works have been seeking to develop online and incremental learning methods. *Online learning* attempts to tackle some predictive tasks by learning from a sequence of data instances one by one at each time [90]. *Incremental learning* is related to online learning, in which input data is continuously utilized to extend the existing model's knowledge [68]. ML methods in this branch have been explored in manufacturing applications to infer causal relationships [10], detect anomalies [242], determine design parameters [255], and validate large-scale machine coordination [239]. Compared to traditional learners, ML models with online/incremental learning capabilities are advocated for building DTs. Their automated update based on new information facilitates the overall system operation and makes the most of real-time data.

### 7.3. Efficient physics-informed learning models with small data

To enhance the usefulness and validity of ML-based DTs, a new topic of ML research termed physics-informed machine learning (PIML) has emerged [77]. PIML refers to a hybridized kind of ML that incorporates process laws and domain constraints into ML models to significantly improve prediction efficiency, accuracy, and transparency while avoiding the reliance on massive training data. Existing PIML works have exploited physical information from the mathematical formulation of physical processes, post-process inspection, and domain knowledge. For example, partial differential equations (PDEs) of melt pool fluid dynamics in metal AM have been incorporated into several ML models to regularize model training, especially optimization algorithms [77].

Pioneering work in developing physics-regularized ML solvers is represented by Physics-Informed NNs (PINN) [201]. PINN is a DL framework for solving forward and inverse problems involving nonlinear PDEs. It leverages deep NNs (DNNs) as universal function approximators to tackle nonlinear process problems without the need to commit to prior assumptions or local time-stepping. This work stemmed from computational physics and involved considerable mathematical formulations and derivations.

The core concept of PINN is to train DNNs to approximate solutions by minimizing the residual of the PDEs and also the initial and boundary conditions [201,218]. Their development represents a milestone for enriching ML with physics and has inspired numerous related works.

Fundamentally, PDML-related research can be pursued in five directions when considering the various stages of ML model development (Fig. 57): (1) physics-informed ML input, 2) physics-regularized model training, 3) physics-informed model component, 4) physics-driven ML architecture, and 5) physics-informed ML output. These directions provide the following benefits:

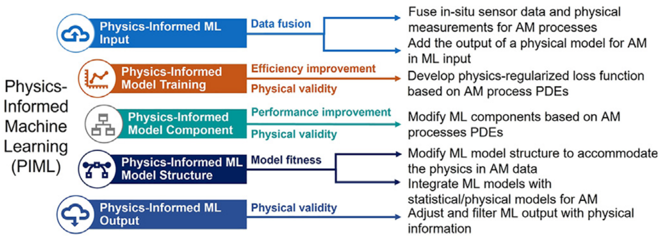


**Fig. 57.** Technical route for PIML.

- Using physical measures or physics-constrained data as ML input helps improve the scientific meanings of ML model decision logic and predictions.
- Guiding model training with physical/domain knowledge improves computational efficiency and data utilization while confining model decision logic with physical laws.
- Modifying ML model components, such as activation functions, with physical knowledge, can facilitate convergence to a physics-informed solution.
- Imbuing ML architectures with prior knowledge enables the combination of ML with physical and mathematical models, as well as the satisfaction of practical constraints.
- Imposing physical constraints on model output penalizes violations of physical laws and improves model consistency with those laws.

### 7.4. Uncertainty-quantified DTs

Uncertainty sources are very common in manufacturing processes. For example, there are 150 process parameters, and each has its variation characteristics during an L-PBF process [93]. The main challenge is that many individual process parameters and the combinations of these parameters may cause uncertainties and propagations along the manufacturing value chain, which significantly influences the accuracy and adaptiveness of a DT in real-time what-if scenarios. The uncertainties can be classified into two categories: aleatory uncertainty and epistemic uncertainty [82]. Since manufacturing process dynamics are critical for product quality and safety, uncertainty quantification (UQ) and model validation are of utmost importance for model-centric process DTs.

Future DTs should address this challenge to account for, describe, and quantify sources of uncertainty associated with process modeling and simulations. From the application perspective, there are many commercially available simulation packages for manufacturing processes. While these are considered the state of practice, they do not support the integration of uncertainty quantification (UQ). Advancement of uncertainty-quantified DTs that model the relationships between process- microstructure-property has the potential to revolutionize progress toward robust DTs. DTs have tremendous potential to unlock a foundational understanding of manufacturing processes, the materials they produce, and the way that materials perform. Integration of UQ tools with DTs will significantly advance the DTs by analysis paradigms.

### 7.5. Ultra-low latency for DT's sensing-learning-control loop

Real-time monitoring, modeling, decision-making, and control of time-critical manufacturing processes require ultra-low latency (in order of milliseconds) communications support with extremely high reliability. 5 G holds the key to this challenging problem due to its unique communication capabilities of ultra-low latency (~1 ms), high data transmission rates (up to 20 Gb/s), high reliability (> 99.999%), high availability, and flexibility (operating many devices simultaneously) [2,205]. However, the diverse and heterogeneous nature of manufacturing processes is characterized by very different applications and use cases, with widely varying requirements. How to fully align 5G-related standardization bodies with the manufacturing industry and how to find the best spectrum usage solution and operator models to meet the specific and distinct requirements of the manufacturing processes are major challenges. Therefore, a new knowledge base needs to be created for sufficient validation of 5G-enabled manufacturing.

In contrast to the conventional static sequential production paradigm, future smart factories will be characterized by a flexible, modular production paradigm that requires powerful and efficient wireless communication and localization services. This is true, in particular, for latency-critical manufacturing processes. For example, chatter in blisk milling is very difficult to real-time monitor and correct while the process is under way because the latency of current sensing technology is too long, which leads to surface defects, and a rework rate as high as 25%, and high cost [37]. While blisk milling is an extreme example, latency-critical manufacturing is generic and ubiquitous as real-time sensing-learning-control is a very common and complicated challenging problem. With the advent of 5 G and future 6 G wireless communication, however, this may change fundamentally, since only 5 G holds the key to this challenging problem due to its unique communication capabilities of ultra-low latency, high speed, high reliability, and flexibility (wireless) to meet the demanding requirements of latency-critical manufacturing [2]. 5G-enabled DTs can provide the degree of ultra-low latency, flexibility, mobility, and versatility that is required for the factories of the future towards a smart, sustainable, and resilient future.

### 7.6. Future prospects of DT within the CIRP community

CIRP has a rich research tradition in developing process models, the core building block of DTs. This paper focuses on the domains of electro-physical, chemical, and photonic processes, but the developed approaches may also apply to other categories of manufacturing processes. In addition to manufacturing processes, DT has broad applications in machine tools, design, assembly, life cycle engineering, and services and optimization. The interdisciplinary knowledge across different STCs will advance the knowledge and development of DTs.

As data is the lifeblood of DTs, expertise in data science and AI/ML is essential for DT development. As CIRP is production-oriented, collaborations between CIRP members and researchers from other communities (e.g., computer science and engineering) can help to address the current major challenges.

Real-time process control is also critical as the final goal of a DT is optimization. Many CIRP members have control expertise, and collaborations between CIRP with communication and control societies are also expected to fully utilize the emerging smart wireless sensors and learning-based control methods for reduced latency.

CIRP is well positioned as an international production society to make the collaborative initiative more effective by creating an essential platform that provides the knowledge infrastructure for engaging, coordinating, and synergizing.

## 8. Summary and conclusions

A DT is defined, fundamentally, as a dynamic digital replica of the prospective, historical, and current behavior of a manufacturing process or physical asset that helps optimize manufacturing performance. The real power of a digital twin − and why it matters so much − is that it can provide a real-time two-way data flow between the physical and digital worlds, which enables autonomous process diagnosis, prognosis, and control that would otherwise be unattainable through current methods. A future DT encompasses five key components: online sensing, data transmission, predictive modeling, decision-making, and real-time control. The key points are summarized as follows.

- A DT framework consists of three main components: a) a process or physical object in the physical world, b) a digital model (e.g., a simulation or data-driven model) in the digital world, and c) the two-way communications (e.g., data flow and proactive control) between the physical and virtual worlds.
- Process models are the core asset of DTs for manufacturing processes. However, a DT is well beyond a process model. The key difference is that a DT not only takes real-time process data but also controls it autonomously through AI/ML. Compared to a vertical process DT, a horizontal object (e.g., products, machines) DT embodies the historical data throughout the entire product lifecycle, in which AI/ML will make possible an intelligent DT.
- From the viewpoint of hierarchy, a DT may evolve through four stages: (1) multi-physics simulation and/or offline data-driven process models (e.g., ML); (2) integration of real-time data with physics-based simulation or data-driven models to incorporate process dynamics and uncertainty; (3) real-time model predictive control (MPC) for manufacturing processes through adjusting a single process parameter; and (4) AI-based autonomous decision-making for real-time process control and optimization.
- From the viewpoint of technology readiness level (TRL), the key components of DT models vary significantly from process to process and object to object. Among the concerned manufacturing processes, DTs of AM processes have the highest TRLs due to their digital nature.
- From the viewpoint of outlook, the major challenges facing future functional DTs include the lack of a federated database management system, the interface between a database and a DT, efficient physics-informed machine learning (PIML) models, uncertainty-quantified process models, and the ultra-low latency for a real-time sensing-learning-control loop.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgments

The paper has been made possible by the contributions and support of CIRP colleagues A. Clare (2), J.P. Kruth (1), M. Kunieda (1), F. Pfefferkorn (1), and M. Schmidt (1). The paper has also been reviewed by M. Grieves (Digital Twin Institute). The comments by W. Zhou (NTU) and U. Küpper (WZL) are appreciated. The primary author would like to thank the US National Science Foundation under CMMI-830922 and CMMI-832822 for contributing to the formulation of the keynote in the context of the digital twin.

## References

[1] 3rd generation partnership project; technical Specification Group Services And System Aspects; Study On Communication For Automation In Vertical Domains, *22.804 3GPP TR*, 2020.
[2] 5G for connected industries and automation, *5G Alliance for Connected Industries and Automation* 2018.
[3] Digital twin market by technology. Type, Industry, And Geography - Global Forecast to 2025. *Market Research Report*, .
[4] https://www.ansys.com/products/digital-twin/ansys-twin-builder, accessed on August 21, 2022.
[5] Advanced Manufacturing Trends To Watch in 2019. www.cbinsights.com, accessed on April 19, 2020.
[6] Acharya R, Sharon JA, Staroselsky A (2017) Prediction Of Microstructure In Laser Powder Bed Fusion Process. *Acta Materialia* 124:360–371.
[7] Akram J, Chalavadi P, Pal D, Stucker B (2018) Understanding Grain Evolution In Additive Manufacturing Through Modeling. *Additive Manufacturing* 21:255–268.
[8] Attar E, Körner C (2011) Lattice Boltzmann Model For Thermal Free Surface Flows With Liquid−Solid Phase Transition. *International Journal of Heat and Fluid Flow* 32(1):156–163.
[9] Ay M, Stemmler S, Schwenzer M, Abel D, Bergs T (2019) odel Predictive Control In Milling Based On Support Vector Machines. *IFAC-PapersOnLine* 52(13):1797–1802.
[10] Baek J-G, Kim C-O, Kim SS (2002) Online Learning Of The Cause-And-Effect Knowledge Of A Manufacturing Process. *International Journal of Production Research* 40(14):3275–3290.
[11] Bartolo P, Lenz E (2006) Computer Simulation Of Stereolithographic Curing Reactions: Phenomenological Versus Mechanistic Approaches. *CIRP Annals* 55 (1):221–225.
[12] Bartolo PJ (2007) Photo-Curing Modelling: Direct Irradiation. *International Journal of Advanced Manufacturing Technology* 32(5):480–491.
[13] Bártolo PJ (2011) Theoretical And Modeling Aspects Of Curing Reactions. in Bártolo P, (Ed.) *Stereolithography*, Springer, Boston, MA.
[14] Bayat M, Mohanty S, Hattel JH (2019) Multiphysics Modelling Of Lack-Of-Fusion Voids Formation And Evolution in IN718 Made By Multi-Track/Multi-Layer L-PBF. *International Journal of Heat & Mass Transfer* 139:95–114.
[15] Behrens A, Ginzel J (2003) Neuro-Fuzzy Process Control System For Sinking EDM. *Journal of Manufacturing Processes* 5(1):33–39.
[16] Bemporad A, Morari M, Dua V, Pistikopoulos EN (2002) The Explicit Linear Quadratic Regulator For Constrained Systems. *Automatica* 38(1):3–20.
[17] Bergs T, Gierlings S, Auerbach T, Klink A, Schraknepper D, Augspurger T (2021) The Concept Of Digital Twin And Digital Shadow In Manufacturing. *Procedia CIRP* 101:81–84.
[18] Bergs T, Harst S (2020) Development Of A Process Signature For Electrochemical Machining. *CIRP Annals* 69(1):153–156.
[19] Bergs T, Heidemanns L, Harst S, Klink A, Klocke F (2018) Evaluation Of Different Short-Cut Methods For The Simulation of PECM Processes. In: *Proc. 14th INSECT*, 131.
[20] Bergs T, Heidemanns L, Klink A (2020) Simulation Assisted Cathode Design For The Manufacturing Of Complex Geometries By Electrochemical Machining (ECM). *Procedia CIRP* 95:688–693.
[21] Bergs T, Mohammadnejad M, Hess R, Heidemanns L, Klink A (2020) Simulation Of The Evolutions In Real Microstructure Of Material Under Thermal Cycle With High Thermal Gradients. *Procedia CIRP* 95:238–243.
[22] Bergs T, Mohammadnejad M, Witteler M, Heidemanns L, Klink A (2020) Experimental Investigation On Process Signature For EDM Processes. *Procedia CIRP* 87:273–278.
[23] Bergs T, Tombul U, Herrig T, Olivier M, Klink A, Klocke F (2018) Analysis Of Characteristic Process Parameters To Identify Unstable Process Conditions During Wire EDM. *Procedia Manufacturing* 18:138–145.
[24] Bisterov I, Abayzeed S, Speidel A, Clare AT (2022) On-Machine Measurement With An Electrochemical Jet Machine Tool. *International Journal of Machine Tools and Manufacture* 174:103859.
[25] Bisterov I, Speidel A, Abayzeed S, Zubyr M, Clare A (2021) Measurement Using Electrolyte Jets. In: *Proc. 17th INSECT*, 73–76.
[26] Bisterov I, Speidel A, Mitchell-Smith J, Clare AT (2021) Implications Of Vector Change In Electrochemical Jet Processing. *Manufacturing Letters* 27:82–86.
[27] Boccadoro M. (2015) Eine leistungssteigernde Innovation für die funkenerosive Bearbeitung, 10. Fachtagung Funkenerosion, Aachen.
[28] Boccadoro M. (2017) Ein Durchbruch in der Drahterosion: Industrielle Anwendungen eines Entladestellensensors, 11. Fachtagung Funkenerosion, Aachen.
[29] Boccadoro M (2018) *Spark Track: A Breakthrough In WEDM, Expert's Corner*, EDM Today, 70–73.
[30] Boccadoro M, D'Amario R, Baumeler M (2020) Towards A Better Controlled Edm: Industrial Applications Of A Discharge Location Sensor In An Industrial Wire Electrical Discharge Machine. *Procedia CIRP* 95:600–604.
[31] Boccadoro M, Dauw D (1995) About The Application Of Fuzzy Controllers In High-Performance Die-Sinking EDM Machines. *CIRP Annals* 44(1):147–150.
[32] Boccadoro M, Drzajic D (2022) About A New Method To Enhance The Productivity Of Die Sinking EDM. *Procedia CIRP* 113:120–124.
[33] Bortels L, Purcar M, Van den Bossche B, Deconinck J (2004) A User-Friendly Simulation Software Tool For 3D ECM. *Journal of Materials Processing Technology* 149 (1-3):486–492.
[34] Boschert S, Rosen R (2016) Digital twin—The Simulation Aspect. *Mechatronic Futures*, Springer, 59–74.
[35] Bottani E, Cammardella A, Murino T, Vespoli S (2017) From the Cyber-Physical System to the Digital Twin: the process development for behaviour modelling of a Cyber Guided Vehicle in M2M logic. *XXII Summer School Francesco TurcoIndustrial Systems Engineering*, 1–7.
[36] Brinksmeier E, Klocke F, Lucca DA, Sölter J, Meyer D (2014) Process Signatures−A New Approach To Solve The Inverse Surface Integrity Problem In Machining Processes. *Procedia CIRP* 13:429–434.
[37] Bussmann M, Bayer E (2007) Market-Oriented Blisk Manufacturing A Challenge For Production Engineering. In: *Proc. of the 1st European Air and Space Conference (CEAS 2007)*, . September 10-13.
[38] Bzdok D, Altman N, Krzywinski M (2018) Points Of Significance: Statistics Versus Machine Learning. *Nature Methods* 15(04):233–234.
[39] Caggiano A, Napolitano F, Teti R (2021) Hierarchical Cluster Analysis For Pattern Recognition Of Process Conditions In Die Sinking EDM process Monitoring. *Procedia CIRP* 99:514–519.
[40] Caggiano A, Napolitano F, Teti R, Bonini S, Maradia U (2020) Advanced Die Sinking EDM Process Monitoring Based On Anomaly Detection For Online Identification Of Improper Process Conditions. *Procedia CIRP* 88:381–386.
[41] Caggiano A, Perez R, Segreto T, Teti R, Xirouchakis P (2016) Advanced Sensor Signal Feature Extraction And Pattern Recognition For Wire EDM Process Monitoring. *Procedia CIRP* 42:34–39.
[42] Caggiano A, Teti R, Perez R, Xirouchakis P (2015) Wire EDM Monitoring For Zero-Defect Manufacturing Based On Advanced Sensor Signal Processing. *Procedia CIRP* 33:315–320.
[43] Castelvecchi D (2016) Can We Open The Black Box Of AI? *Nature News* 538 (7623):20.

[44] Cichocki A, Zdunek R, Phan AH, Amari S-i (2009) *Nonnegative Matrix and Tensor Factorizations: Applications to Exploratory Multi-Way Data Analysis and Blind Source Separation*, John Wiley & Sons.
[45] Cimino C, Negri E, Fumagalli L (2019) Review Of Digital Twin Applications In Manufacturing. *Computers in Industry* 113:103130.
[46] Columbus L (2019) Making Digital Twins Work In The Real World. *Industry Week* . Nov. 26.
[47] Corradini F, Silvestri M (2022) Design And Testing Of A Digital Twin For Monitoring And Quality Assessment Of Material Extrusion Process. *Additive Manufacturing* 51:102633.
[48] D'Addona DM, Ullah A, Matarazzo D (2017) Tool-Wear Prediction And Pattern-Recognition Using Artificial Neural Network And DNA-Based Computing. *Journal of Intelligent Manufacturing* 28(6):1285–1301.
[49] Danilov I, Paul R, Hackert-Oschätzchen M, Zinecker M, Quitzke S, Schubert A (2020) Random Sequential Simulation Of The Resulting Surface Roughness In Plasma Electrolytic Polishing Of Stainless Steel. *Procedia CIRP* 95:981–986.
[50] De Baere D, Bayat M, Mohanty S, Hattel J (2018) Thermo-Fluid-Metallurgical Modelling Of The Selective Laser Melting Process Chain. *Procedia CIRP* 74:87–91.
[51] Debroy T, Zhang W, Turner J, Babu SS (2017) Building Digital Twins Of 3D Printing Machines. *Scripta Materialia* 135:119–124.
[52] Dehoff RR, Kirka M, Sames W, Bilheux H, Tremsin A, Lowe L, Babu S (2015) Site Specific Control Of Crystallographic Grain Orientation Through Electron Beam Additive Manufacturing. *Materials Science and Technology* 31 (8):931–938.
[53] Denlinger ER, Irwin J, Michaleris P (2014) Thermomechanical Modeling Of Additive Manufacturing Large Parts. *Journal of Manufacturing Science and Engineering* 136(6):061007.
[54] Dewulf W, Pavan M, Craeghs T, Kruth J-P (2016) Using X-Ray Computed Tomography To Improve The Porosity Level Of Polyamide-12 Laser Sintered Parts. *CIRP Annals* 65(1):205–208.
[55] Di Campli R, Maradia U, Boccadoro M, D'Amario R, Mazzolini L (2020) Real-Time Wire EDM Tool Simulation Enabled By Discharge Location Tracker. *Procedia CIRP* 95:308–312.
[56] Doan A, Halevy A, Ives Z (2012) *Principles of Data Integration*, Elsevier.
[57] Držajića D, Wiessner M, Maradia U, Piga D (2022) Virtual Operators With Self And Transfer Learning Ability In EDM. *Procedia CIRP* 113:17–22.
[58] El Halabi F, Gonzalez D, Chico-Roca A, Doblare M (2013) Multiparametric Response Surface Construction By Means Of Proper Generalized Decomposition: An Extension Of The PARAFAC Procedure. *Computer Methods in Applied Mechanics and Engineering* 253:543–557.
[59] Ernst A, Heib T, Hall T, Schmidt G, Bähre D (2017) Simulation-Based Tool Development For The Electrochemical Machining Of Jet Engine Vanes. In: *Proc. 13th INSECT*, 23–30.
[60] Fernandez RC, Abedjan Z, Koko F, Yuan G, Madden S, Stonebraker M (2018) Aurum: A Data Discovery System. *IEEE 34th ICDE*, 1001–1012.
[61] Fischer P, Romano V, Weber H-P, Karapatis N, Boillat E, Glardon R (2003) Sintering Of Commercially Pure Titanium Powder With A Nd: YAG Laser Source. *Acta Materialia* 51(6):1651–1662.
[62] Fuller A, Fan Z, Day C, Barlow C (2020) Digital Twin: Enabling Technologies, Challenges And Open Research. *IEEE Access* 8:108952–108971.
[63] Gaikwad A, Yavari R, Montazeri M, Cole K, Bian L, Rao P (2020) Toward The Digital Twin Of Additive Manufacturing: Integrating Thermal Simulations, Sensing, And Analytics To Detect Process Faults. *IISE Transactions* 52 (11):1204–1217.
[64] Ganeriwala R, Zohdi TI (2014) Multiphysics Modeling And Simulation Of Selective Laser Sintering Manufacturing Processes. *Procedia CIRP* 14:299–304.
[65] Gao RX, Wang L, Helu M, Teti R (2020) Big Data Analytics For Smart Factories Of The Future. *CIRP Annals* 69(2):668–692.
[66] Garetti M, Rosa P, Terzi S (2012) Life Cycle Simulation For The Design Of Product–Service Systems. *Computers in Industry* 63(4):361–369.
[67] Garg S, Guizani M, Guo S, Verikoukis C (2019) Guest Editorial Special Section On AI-Driven Developments In 5G-envisioned Industrial Automation: Big Data Perspective. *IEEE Transactions on Industrial Informatics* 16 (2):1291–1295.
[68] Gepperth A, Hammer B (2016) Incremental Learning Algorithms And Applications. *European Symposium On Artificial Neural Networks (ESANN)*, .
[69] Giusti A, Dotta M, Maradia U, Boccadoro M, Gambardella LM, Nasciuti A (2020) Image-Based Measurement Of Material Roughness Using Machine Learning Techniques. *Procedia CIRP* 95:377–382.
[70] Glaessgen E, Stargel D (2012) The Digital Twin Paradigm For Future NASA and US Air Force Vehicles. *53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference*, 1818.
[71] Grieves M (2002) Completing The Cycle: Using PLM Information In The Sales And Service Functions. *SME Management Forum*, .
[72] Grieves M (2011) *Driving Innovative and Lean Products Through Product Lifecycle Management*, Space Coast PressCocoa Beach, FL.
[73] Grieves M (2022) Intelligent Digital Twins And The Development And Management Of Complex Systems. *Digital Twin* 2(8):8.
[74] Grieves M, Vickers J, Kahlen F-J, Flumerfelt S (2017) Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior In Complex Systems. in Alves A, (Ed.) *Trans-Disciplinary Perspectives on System Complexity*, Springer: Switzerland, 85–114.
[75] Gulwani S, Polozov O, Singh R (2017) Program Synthesis. *Foundations and Trends® in Programming Languages* 4(1-2):1–119.
[76] Gunasegaram D, Murphy A, Barnard A, DebRoy T, Matthews M, Ladani L, Gu D (2021) Towards Developing Multiscale-Multiphysics Models And Their Surrogates For Digital Twins Of Metal Additive Manufacturing. *Additive Manufacturing* 46:102089.
[77] Guo W, Tian Q, Guo S, Guo Y (2020) A Physics-Driven Deep Learning Model For Process-Porosity Causal Relationship And Porosity Prediction With Interpretability In Laser Metal Deposition. *CIRP Annals* 69(1):205–208.
[78] Gürtler F-J, Karg M, Leitz K-H, Schmidt M (2013) Simulation Of Laser Beam Melting Of Steel Powders Using The Three-Dimensional Volume Of Fluid Method. *Physics Procedia* 41:881–886.
[79] Hackert-Oschätzchen M, Paul R, Kowalick M, Kuhn D, Meichsner G, Zinecker M, Schubert A (2017) Characterization Of An Electrochemical Machining Process For Precise Internal Geometries By Multiphysics Simulation. *Procedia CIRP* 58:175–180.
[80] Hackert-Oschätzchen M, Paul R, Kowalick M, Martin A, Meichsner G, Schubert A (2015) Multiphysics Simulation Of The Material Removal In Jet Electrochemical Machining. *Procedia CIRP* 31:197–202.
[81] Haeri S, Wang Y, Ghita O, Sun J (2017) Discrete Element Simulation And Experimental Study Of Powder Spreading Process In Additive Manufacturing. *Powder Technology* 306:45–54.
[82] Haldar A, Mahadevan S (2000) *Probability, reliability, and Statistical Methods in Engineering Design*, John Wiley & Sons Incorporated.
[83] Han F, Kunieda M, Asano H (2004) Improvement Of Controllability Of Discharge Locations In WEDM. *Journal of The Japan Society of Electrical Machining Engineers* 38(87):31–36.
[84] Han F, Kunieda M, Sendai T, Imai Y (2002) High Precision Simulation Of WEDM Using Parametric Programming. *CIRP Annals* 51(1):165–168.
[85] Hastie T, Tibshirani R, Friedman JH, Friedman JH (2009) *The Elements of Statistical learning: Data mining, inference, and Prediction*, Springer.
[86] Heidemanns L, Herrig T, Klink A (2022) Advancing Electrochemical Machining By The Use Of Additive Manufacturing For Cathode Production. *Procedia CIRP* 112:328–333.
[87] Hermann F, Chen B, Ghasemi G, Stegmaier V, Ackermann T, Reimann P, Vogt S, Graf T, Weyrich M (2022) A Digital Twin Approach For The Prediction Of The Geometry Of Single Tracks Produced By Laser Metal Deposition. *Procedia CIRP* 107:83–88.
[88] Hess R, Grethe P, Heidemanns L, Herrig T, Klink A, Bergs T (2022) Simulation Based Derivation Of Rim Zone Properties Caused By Thermal Loadings During EDM Process. *Procedia CIRP* 113:41–46.
[89] Hinduja S, Kunieda M (2013) Modelling of ECM And EDM Processes. *CIRP Annals* 62(2):775–797.
[90] Hoi SC, Sahoo D, Lu J, Zhao P (2018) Online Learning: A Comprehensive Survey.
[91] Holsten M, Klink A, Bergs T (2019) Concepts For Advancing The Use Of Process Data In Electrical Discharge Machining. *Procedia CIRP* 82:220–223.
[92] Howells R. (2018) The Rise Of The Digital Twin, Digital Supply Networks. https://www.digitalistmag.com/digital-supply-networks/2018/06/27/rise-of-digital-twin-06177716. accessed on June 10, 2019.
[93] Hu Z, Mahadevan S (2017) Uncertainty Quantification In Prediction Of Material Properties During Additive Manufacturing. *Scripta Materialia* 135:135–140.
[94] Huang G, Xia W, Qin L, Zhao W (2018) Online Workpiece Height Estimation For Reciprocated Traveling Wire EDM Based On Support Vector Machine. *Procedia CIRP* 68:126–131.
[95] Ibáñez R, Abisset-Chavanne E, Ammar A, González D, Cueto E, Huerta A, Duval JL, Chinesta F (2018) A Multidimensional Data-Driven Sparse Identification Technique: The Sparse Proper Generalized Decomposition. *Complexity* . 2018.
[96] Ilyas IF, Chu X (2019) Data Cleaning. *Morgan & Claypool* .
[97] Indurkhya G, Rajurkar K (1992) Artificial Neural Network Approach In Modelling Of EDM Process. In: *Proc. of the 1992 Artificial Neural Networks in Engineering, ANNIE'92*, St. Louis, MO, USA845–850.
[98] Jagadish H, Chapman A, Elkiss A, Jayapandian M, Li Y, Nandi A, Yu C (2007) Making Database Systems Usable. In: *Proc. SIGMOD'07*, 13–24.
[99] Jennes M, Snoeys R, Dekeyser W (1984) Comparison Of Various Approaches To Model The Thermal Load On The EDM-Wire Electrode. *CIRP Annals* 33 (1):93–98.
[100] Jiang L, Yu L, Premaratne P, Zhang Z, Qin H (2021) CFD-Based Numerical Modeling To Predict The Dimensions Of Printed Droplets In Electrohydrodynamic Ink-jet Printing. *Journal of Manufacturing Processes* 66:125–132.
[101] Kabaldin YG, Kolchin P, Shatagin D, Anosov M, Chursin A (2019) Digital Twin For 3D Printing On CNC Machines. *Russian Engineering Research* 39 (10):848–851.
[102] Kapteyn MG, Knezevic DJ, Huynh D, Tran M, Willcox KE (2022) Data-Driven Physics-Based Digital Twins Via A Library Of Component-Based Reduced-Order Models. *International Journal for Numerical Methods in Engineering* 123 (13):2986–3003.
[103] Karges F, Zeis M, Hoffmeister F, Feiling N, Niegl M (2018) Analysis Of The Suitability Of Frontal Gap Experiments As A Basis For The Simulation Of Complex Shaped Parts In ECM. In: *Proc. 14th INSECT*, 139–144.
[104] Karpatne A, Atluri G, Faghmous JH, Steinbach M, Banerjee A, Ganguly A, Shekhar S, Samatova N, Kumar V (2017) Theory-Guided Data Science: A New Paradigm For Scientific Discovery From Data. *IEEE Transactions on Knowledge and Data Engineering* 29(10):2318–2331.
[105] Karpuschewski B, Kinner-Becker T, Klink A, Langenhorst L, Mayer J, Meyer D, Radel T, Reese S, Sölter J (2022) Process Signatures–Knowledge-Based Approach Towards Function-Oriented Manufacturing. *Procedia CIRP* 108:624–629.
[106] Keller T, Lindwall G, Ghosh S, Ma L, Lane BM, Zhang F, Kattner UR, Lass EA, Heigel JC, Idell Y (2017) Application Of Finite Element, Phase-Field, And CALPHAD-Based Methods To Additive Manufacturing Of Ni-Based Superalloys. *Acta Materialia* 139:244–253.

[107] Kimura S, Iwai H, Liu S, Okada A, Kurihara H (2022) Influence Of Nozzle Jet Flushing In Wire EDM Of Workpiece With Stepped Thickness. *Procedia CIRP* 113:149–154.
[108] Kitamura T, Kunieda M, Abe K (2015) Observation Of Relationship Between Bubbles And Discharge Locations In EDM Using Transparent Electrodes. *Precision Engineering* 40:26–32.
[109] Klingaa CG, Mohanty S, Funch CV, Hjermitslev A, Haahr-Lillevang L, Hattel JH (2021) Towards A Digital Twin Of Laser Powder Bed Fusion With A Focus On Gas Flow Variables. *Journal of Manufacturing Processes* 65:312–327.
[110] Klink A, Heidemanns L, Rommes B (2020) Study Of The Electrolyte Flow At Narrow Openings During Electrochemical Machining. *CIRP Annals* 69 (1):157–160.
[111] Klink A, Holsten M, Schneider S, Koshy P (2016) Acoustic Emission Signatures Of Electrical Discharge Machining. *CIRP Annals* 65(1):229–232.
[112] Klink A, Schneider S, Bergs T (2022) Development Of A Process Signature For Electrical Discharge Machining. *CIRP Annals* 71(1):177–180.
[113] Klocke F, Harst S, Karges F, Zeis M, Klink A (2017) Modeling Of The Electrochemical Dissolution Process For A Two-Phase Material In A Passivating Electrolyte System. *Procedia CIRP* 58:169–174.
[114] Klocke F, Heidemanns L, Zeis M, Kling A (2017) Clarification Of Gap Phenomena In Precise Electrochemical Machining By Implementing A "Virtual Sensor". In: *Proc. 13th INSECT*, 16–22.
[115] Klocke F, Heidemanns L, Zeis M, Klink A (2018) A Novel Modeling Approach For The Simulation Of Precise Electrochemical Machining (PECM) with pulsed current and oscillating cathode. *Procedia CIRP* 68:499–504.
[116] Klocke F, Klink A (2015) Funkenerosion und elektrochemische bearbeitung – prozesstechnologische potentiale im kontext der digitalisierten produktion, 15. *Internationales Kolloquium "Werkzeugbau mit Zukunft", Aachen* . November 11-12, 2015.
[117] Klocke F, Klink A, Veselovac D, Aspinwall DK, Soo SL, Schmidt M, Schilp J, Levy G, Kruth J-P (2014) Turbomachinery Component Manufacture By Application Of Electrochemical, Electro-Physical And Photonic Processes. *CIRP Annals* 63 (2):703–726.
[118] Klocke F, Raabe R, Wiesner G (1997) Neuro-Fuzzy Approach For Electro-Discharge Sinking Process Control. *International Conference on Computational Intelligence*, Springer, , 587–588.
[119] Klocke F, Welling D, Klink A, Perez R (2014) Quality Assessment Through In-Process Monitoring Of Wire-EDM For Fir Tree Slot Production. *Procedia CIRP* 24:97–102.
[120] Klocke F, Zeis M, Herrig T, Harst S, Klink A (2014) Optical In Situ Measurements And Interdisciplinary Modeling Of The Electrochemical Sinking Process Of inconel 718. *Procedia CIRP* 24:114–119.
[121] Klocke F, Zeis M, Klink A (2015) Interdisciplinary Modelling Of The Electrochemical Machining Process For Engine Blades. *CIRP Annals* 64(1):217–220.
[122] Klotz M (2019) *Big Data Analysen Bei Der Funkenerosion in Der Großserie, Fachtagung Funkenerosion*, RWTH Aachen University. Aachen Nov. 26-27.
[123] Knapp G, Mukherjee T, Zuback J, Wei H, Palmer T, De A, DebRoy T (2017) Building Blocks For A Digital Twin Of Additive Manufacturing. *Acta Materialia* 135:390–399.
[124] Koepf JA, Gotterbarm MR, Markl M, Körner C (2018) 3D Multi-Layer Grain Structure Simulation Of Powder Bed Fusion Additive Manufacturing. *Acta Materialia* 152:119–126.
[125] Kohli M, Chen T, Dastjerdi MB, Welles J, Seskar I, Krishnaswamy H, Zussman G (2020) Open-Access Full-Duplex Wireless in the ORBIT and COSMOS Testbeds. In: *Proc. WiNTECH'20*, 9–16.
[126] Kojima H, Kunieda M, Nishiwaki N (1992) Understanding Discharge Location Movements During EDM. In: *Proc. ISEM*, 144–149.
[127] Körner C, Attar E, Heinl P (2011) Mesoscopic Simulation Of Selective Beam Melting Processes. *Journal of Materials Processing Technology* 211(6):978–987.
[128] Körner C, Bauereiß A, Attar E (2013) Fundamental Consolidation Mechanisms During Selective Beam Melting Of Powders. *Modelling and Simulation in Materials Science* 21(8):085011.
[129] Körner C, Helmer H, Bauereiß A, Singer RF (2014) Tailoring The Grain Structure of IN718 During Selective Electron Beam Melting. *MATEC Web of Conferences*, 08001.
[130] Kritzinger W, Karner M, Traar G, Henjes J, Sihn W (2018) Digital Twin In Manufacturing: A Categorical Literature Review And Classification. *IFAC-PapersOnLine* 51(11):1016–1022.
[131] Kronauer S, Mavkov B, Mejari M, Piga D, Jaques F, D'Amario R, Di Campli R, Nasciuti A (2022) Data-Driven Statistical Analysis For Discharge Position Prediction On Wire EDM. *Procedia CIRP* 113:143–148.
[132] Kuhn T (2017) Digitaler Zwilling. *Informatik-Spektrum* 40(5):440–444.
[133] Kundin J, Mushongera L, Emmerich H (2015) Phase-Field Modeling Of Microstructure Formation During Rapid Solidification In Inconel 718 Superalloy. *Acta Materialia* 95:343–356.
[134] Kunieda M, Kaneko Y, Natsu W (2012) Reverse Simulation Of Sinking EDM Applicable To Large Curvatures. *Precision Engineering* 36(2):238–243.
[135] Kunieda M, Kojima H, Kinoshita N (1990) On-Line Detection of EDM Spark Locations By Multiple Connection Of Branched Electric Wires. *CIRP Annals* 39 (1):171–174.
[136] Kunieda M, Kowaguchi W, Takita T (1999) Reverse Simulation Of Die-Sinking EDM. *CIRP Annals* 48(1):115–118.
[137] Kunieda M, Takeshita S, Okumiya K (1998) Study On Wire Electrode Temperature In WEDM. In: *Proc. ISEM*, 119–128.
[138] Küpper U, Herrig T, Bergs T (2021) Visualization Of Spatially Resolved Energy In Wire Electrical Discharge Machining. *Procedia CIRP* 104:1512–1517.
[139] Küpper U, Herrig T, Klink A, Welling D, Bergs T (2020) Evaluation Of The Process Performance In Wire EDM Based On An Online Process Monitoring System. *Procedia CIRP* 95:360–365.
[140] Küpper U, Tchoupe E, Klink A, Bergs T (2022) Prediction Of Geometrical Accuracy In Wire EDM By Analyzing Process Data. *Procedia CIRP* 113:23–28.
[141] Lauwers B, Kruth J-P, Bleys P, Van Coppenolle B, Stevens L, Derighetti R (1998) Wire Rupture Prevention Using On-Line Pulse Localisation In WEDM. In: *Proc. 12th ISEM*, 203–213.
[142] Lee J, Bagheri B, Kao H-A (2015) A Cyber-Physical Systems Architecture For Industry 4.0-Based Manufacturing Systems. *Manufacturing Letters* 3:18–23.
[143] Lee J, Lapira E, Bagheri B, Kao H-a (2013) Recent Advances And Trends In Predictive Manufacturing Systems In Big Data Environment. *Manufacturing Letters* 1 (1):38–41.
[144] Lee Y, Zhang W (2016) Modeling Of Heat Transfer, Fluid Flow And Solidification Microstructure Of Nickel-Base Superalloy Fabricated By Laser Powder Bed Fusion. *Additive Manufacturing* 12:178–188.
[145] Li C, Liu Z, Fang X, Guo Y (2018) On The Simulation Scalability Of Predicting Residual Stress And Distortion In Selective Laser Melting. *Journal of Manufacturing Science and Engineering* 140(4):041013.
[146] Li C-J, Tsai T-W, Tseng C-C (2016) Numerical Simulation For Heat And Mass Transfer During Selective Laser Melting Of Titanium Alloys Powder. *Physics Procedia* 83:1444–1449.
[147] Li D, Cao H, Zhang X, Chen X, Yan R (2019) Model Predictive Control Based Active Chatter Control In Milling Process. *Mechanical Systems and Signal Processing* 128:266–281.
[148] Li Y, Xu K, Liu X, Yang M, Gao J, Maropoulos P (2021) Stress-Oriented 3D Printing Path Optimization Based On Image Processing Algorithms For Reinforced Load-Bearing Parts. *CIRP Annals* 70(1):195–198.
[149] Li Z, Li W, Cao B, Liu Y, Dai Y (2022) Simulation And Experiment of ECM Accuracy Of Cooling Holes Considering The Influence Of Temperature Field. *Case Studies in Thermal Engineering* 35:102112.
[150] Liu C, Le Roux L, Körner C, Tabaste O, Lacan F, Bigot S (2020) Digital Twin-Enabled Collaborative Data Management For Metal Additive Manufacturing Systems. *Journal of Manufacturing Systems* .
[151] Liu J, Guo Y (2016) Modeling Of White Layer Formation In Electric Discharge Machining (Edm) By Incorporating Massive Random Discharge Characteristics. *Procedia CIRP* 42:697–702.
[152] Liu J, Guo Y (2016) Thermal Modeling of EDM With Progression Of Massive Random Electrical Discharges. *Procedia Manufacturing* 5:495–507.
[153] Liu X, Kang X, Xi X, Liang W, Zhao W (2013) Electrode Feed Path Planning For Multi-Axis EDM Of Integral Shrouded Impeller. *International Journal of Advanced Manufacturing Technology* 68(5):1697–1706.
[154] Liu X, Kang X, Zhao W, Liang W (2013) Electrode Feeding Path Searching For 5-Axis EDM Of Integral Shrouded Blisks. *Procedia CIRP* 6:107–111.
[155] Liu Y, Liu J, Zhu D, Wang H (2022) Design And Optimization Of Electrolyte Flow Fields In Electrochemical Machining Of Cross-Channel Array With Tool Vibration. *Chinese Journal of Aeronautics* 35(4):461–472.
[156] Liu Z, Guo Y (2018) A Hybrid Approach To Integrate Machine Learning And Process Mechanics For The Prediction Of Specific Cutting Energy. *CIRP Annals* 67 (1):57–60.
[157] Loebel S, Hackert-Oschätzchen M, Meichsner G, Petzold T, Zinecker M, Schubert A (2019) Modelling of Precise Electrochemical Machining For Nickel-Based Centrifugal Impellers. In: *Proc. 15th INSECT*, 193.
[158] Loebel S, Hackert-Oschätzchen M, Meichsner G, Zinecker M, Schubert A (2018) Simulation-Based Design Of Electrochemical Machining Processes For Microstructuring Of High-Strength Materials. In: *Proc. 14th INSECT*, 145–154.
[159] Loebel S, Petzhold T, Steinert P, Zinecker M, Schubert A (2020) Order Reduction Of Simulation Models For The Precuise Electrochemical Machining Of Centrifugal Impellers. In: *Proc. 16th INSECT*, 117–122.
[160] Loebel S, Zinecker M, Steinert P, Schubert A (2022) Transient Simulation Of Electrochemical Machining Processes For Manufacturing Of Surface Structures In High-Strength Materials. *Engineering Reports* 4(7-8):e12360.
[161] Mahoney TC, Kota S (2020) *Smart Manufacturing*: A Primer For Small Manufacturers,, MForesight Report number: MF-TR-2020-0301.
[162] Mallinson S, Aquino A d A, McBain G, Horrocks G, Barber T, de Silva C, Yeoh G (2022) Three-Dimensional Numerical Simulation Of Air-Flow In Inkjet Print-Zones. *International Journal of Heat and Fluid Flow* 93:108911.
[163] Manière C, Kerbart G, Harnois C, Marinel S (2020) Modeling Sintering Anisotropy In Ceramic Stereolithography Of Silica. *Acta Materialia* 182:163–171.
[164] Manvatkar V, De A, DebRoy T (2014) Heat Transfer And Material Flow During Laser Assisted Multi-Layer Additive Manufacturing. *Journal of Applied Physics* 116(12):124905.
[165] Maradia U, Benavoli A, Boccadoro M, Bonesana C, Klyuev M, Zaffalon M, Gambardella L, Wegenerc K (2018) EDM Drilling Optimisation Using Stochastic Techniques. *Procedia CIRP* 67(1):350–355.
[166] Maradia U, Knaak R, Busco WD, Boccadoro M, Stirnimann J, Wegener K (2015) Spark Location Adaptive Process Control In Meso-Micro EDM. *International Journal of Advanced Manufacturing Technology* 81(9):1577–1589.
[167] Marchese K (2023) Digital thread for additive manufacturing. https://www2.deloitte.com/us/en/pages/public-sector/articles/digital-thread.html, accessed on March 10, 2023.
[168] Markl M, Körner C (2015) Free Surface Neumann Boundary Condition For The Advection–Diffusion Lattice Boltzmann Method. *Journal of Computational Physics* 301:230–246.
[169] Matias JM, Bartolo PJ, Pontes AV (2009) Modeling And Simulation Of Photofabrication Processes Using Unsaturated Polyester Resins. *Journal of Applied Polymer Science* 114(6):3673–3685.

[170] Matthews S. (2018) Designing better machines: the evolution of the digital twin explained, Keynote Delivered at Hannover Messe, Germany. https://www.ibm.com/blogs/internet-of-things/iot-evolution-of-a-cognitive-digital-twin/, accessed on May 15, 2021.
[171] Meier C, Penny RW, Zou Y, Gibbs JS, Hart AJ (2017) Thermophysical Phenomena In Metal Additive Manufacturing By Selective Laser Melting: Fundamentals, Modeling, Simulation And Experimentation.
[172] Mercelis P, Kruth JP (2006) Residual Stresses In Selective Laser Sintering And Selective Laser Melting. *Rapid Prototyping Journal* 12(5):254–265.
[173] Michaleris P (2014) Modeling Metal Deposition In Heat Transfer Analyses Of Additive Manufacturing Processes. *Finite Elements in Analysis and Design* 86:51–60.
[174] Microsoft (2019) Manufacturing Trends Report 2019.
[175] Mies D, Marsden W, Warde S (2016) Overview Of Additive Manufacturing Informatics: "A Digital Thread. *Integrating Materials and Manufacturing Innovation* 5 (1):114–142.
[176] Miller R, Cao G, Grujicic M (2001) Monte Carlo Simulation Of Three-Dimensional Nonisothermal Grain-Microstructure Evolution: Application to LENS Rapid Fabrication. *Journal of Materials Synthesis and Processing* 9(6):329–345.
[177] Miller RJ (2018) Open Data Integration. *Proceedings VLDB Endowment* 11 (12):2130–2139.
[178] Min Q, Lu Y, Liu Z, Su C, Wang B (2019) Machine Learning Based Digital Twin Framework For Production Optimization In Petrochemical Industry. *International Journal of Information Management* 49:502–519.
[179] Miskinis C (2019) The History And Creation Of The Digital Twin Concept. *Challenge Advisory*. https://www.challenge.org/insights/digital-twin-history/, accessed on March 10, 2022.
[180] Morimoto K, Kunieda M (2009) Sinking EDM Simulation By Determining Discharge Locations Based On Discharge Delay Time. *CIRP Annals* 58(1):221–224.
[181] Mourtzis D, Togias T, Angelopoulos J, Stavropoulos P (2021) A Digital Twin Architecture For Monitoring And Optimization Of Fused Deposition Modeling Processes. *Procedia CIRP* 103:97–102.
[182] Mussomeli A, Meeker B, Shepley S, Schatsky D (2018) Signals For Strategists: Expecting Digital Twins. *Deloitte Insights* .
[183] Negri E, Fumagalli L, Macchi M (2017) A review Of The Roles Of Digital Twin In CPS-Based Production Systems. *Procedia Manufacturing* 11:939–948.
[184] Pal D, Patil N, Zeng K, Stucker B (2014) An Integrated Approach To Additive Manufacturing Simulations Using Physics Based, Coupled Multiscale Process Modeling. *Journal of Manufacturing Science and Engineering* 136(6):061022.
[185] Panetta K. (2018) Gartner Top 10 Strategic technology Trends For 2019, https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2019/, accessed on May 22, 2021.
[186] Panwisawas C, Qiu C, Anderson MJ, Sovani Y, Turner RP, Attallah MM, Brooks JW, Basoalto HC (2017) Mesoscale Modelling Of Selective Laser Melting: Thermal Fluid Dynamics And Microstructural Evolution. *Computation Materials Science* 126:479–490.
[187] Parrott A, Warshaw L (2017) Industry 4.0 And The Digital Twin. *Deloitte Insights* .
[188] Parteli EJ, Pöschel T (2016) Particle-Based Simulation Of Powder Application In Additive Manufacturing. *Powder Technology* 288:96–102.
[189] Paul A, Roy SS (2022) Numerical Simulation To Predict Printed Width In EHD Inkjet 3D Printing Process. *Materials Today: Proceedings* 62:373–379.
[190] Paul R, Hackert-Oschätzchen M, Danilov I, Zanjani MY, Schubert A (2019) 3D Multiphysics Simulation Of Jet Electrochemical Machining Of Intersecting Line Removals. *Procedia CIRP* 82:196–201.
[191] Paul S, Liu J, Strayer ST, Zhao Y, Sridar S, Klecka MA, Xiong W, To AC (2020) A Discrete Dendrite Dynamics Model For Epitaxial Columnar Grain Growth In Metal Additive Manufacturing With Application To inconel. *Additive Manufacturing* 36:101611.
[192] Percoco G, Arleo L, Stano G, Bottiglione F (2021) Analytical Model To Predict The Extrusion Force As A Function Of The Layer Height, In Extrusion Based 3D Printing. *Additive Manufacturing* 38:101791.
[193] Phua A, Davies C, Delaney G (2022) A Digital Twin Hierarchy For Metal Additive Manufacturing. *Computers in Industry* 140:103667.
[194] Piascik B, Vickers J, Lowry D, Scotti S, Stewart J, Calomino A (2012) Materials, Structures, Mechanical Systems, And Manufacturing Roadmap. *NASA* .
[195] Prabhakar P, Sames WJ, Dehoff R, Babu SS (2015) Computational Modeling Of Residual Stress Formation During The Electron Beam Melting Process For Inconel 718. *Additive Manufacturing* 7:83–91.
[196] Qi Q, Tao F, Hu T, Anwer N, Liu A, Wei Y, Wang L, Nee A (2021) Enabling Technologies And Tools For Digital Twin. *Journal of Manufacturing Systems* 58:3–21.
[197] Qi Q, Tao F, Zuo Y, Zhao D (2018) Digital Twin Service Towards Smart Manufacturing. *Procedia CIRP* 72:237–242.
[198] Qian C, Hu K, Li J, Li P, Lu Z (2021) The Effect Of Light Scattering In Stereolithography Ceramic Manufacturing. *Journal of the European Ceramic Society* 41 (14):7141–7154.
[199] Raghavan N, Dehoff R, Pannala S, Simunovic S, Kirka M, Turner J, Carlson N, Babu SS (2016) Numerical Modeling Of Heat-Transfer And The Influence Of Process Parameters On Tailoring The Grain Morphology of IN718 In Electron Beam Additive Manufacturing. *Acta Materialia* 112:303–314.
[200] Rai A, Markl M, Körner C (2016) A coupled Cellular Automaton–Lattice Boltzmann Model For Grain Structure Simulation During Additive Manufacturing. *Computation Materials Science* 124:37–48.
[201] Raissi M, Perdikaris P, Karniadakis GE (2019) Physics-Informed Neural Networks: A Deep Learning Framework For Solving Forward And Inverse Problems Involving Nonlinear Partial Differential Equations. *Journal of Computational Physics* 378:686–707.
[202] Rawlings JB (2000) Tutorial overview of model predictive control. *IEEE Control Systems Magazine* 20(3):38–52.
[203] Rodgers TM, Madison JD, Tikare V (2017) Simulation Of Metal Additive Manufacturing Microstructures Using Kinetic Monte Carlo. *Computation Materials Science* 135:78–89.
[204] Rosen R, Von Wichert G, Lo G, Bettenhausen KD (2015) About The Importance Of Autonomy And Digital Twins For The Future Of Manufacturing. *IFAC-PapersOnLine* 48(3):567–572.
[205] Sachs J, Wallstedt K, Alriksson F, Eneroth G (2019) Boosting Smart Manufacturing With 5G Wireless Connectivity. *Ericsson Tech Reviews* 2:1–12.
[206] Saeedi J, Dotta M, Galli A, Nasciuti A, Maradia U, Boccadoro M, Gambardella LM, Giusti A (2021) Measurement And Inspection Of Electrical Discharge Machined Steel Surfaces Using Deep Neural Networks. *Machine Vision and Applications* 32 (1):1–15.
[207] Saxena KK, Wu M, Chen X, Qian J, Reynaerts D (2020) Multiphysics Simulation Enabled 'Virtual Sensing' Approach For Monitoring The Parameters In The Inter-electrode Gap During Tool-Based Hybrid Laser-Electrochemical Micromachining. In: *Proc. 16th INSECT*, 95–104.
[208] Schaarschmidt I, Zinecker M, Hackert-Oschätzchen M, Meichsner G, Schubert A (2017) Multiscale Multiphysics Simulation Of A Pulsed Electrochemical Machining Process With Oscillating Cathode For Microstructuring Of Impact Extrusion Punches. *Procedia CIRP* 58:257–262.
[209] Schneider S, Herrig T, Klink A, Bergs T (2022) Modeling Of The Temperature Field Induced During Electrical Discharge Machining. *CIRP Journal of Manufacturing Science and Technology* 38:650–659.
[210] Schneider S, Vorspohl J, Frerichs F, Klink A, Meinke M, Schröder W, Lübben T (2021) Investigation On Residual Stress Induced By Multiple EDM Discharges. *Procedia CIRP* 102:482–487.
[211] Schurov S, Maradia U, Perez R (2019) *AI Applications In Machine Tools*, Matlab ExpoSwitzerland.
[212] Scime L, Singh A, Paquit V (2022) A Scalable Digital Platform For The Use Of Digital Twins In Additive Manufacturing. *Manufacturing Letters* 31:28–32.
[213] Shafto M, Conroy M, Doyle R, Glaessgen E, Kemp C, LeMoigne J, Wang L (2012) Modeling, Simulation, Information Technology & Processing Roadmap. *NASA* 32:1–38.
[214] Shi W, Cao J, Zhang Q, Li Y, Xu L (2016) Edge Computing: Vision And Challenges. *IEEE Internet of Things Journal* 3(5):637–646.
[215] Shibata K, Kunieda M (2019) In-Process Simulation Of Wire Electrode Displacement In WEDM Using Optical Sensor. *Journal of the Japan Society for Precision Engineering* 85(10):879–884.
[216] Shibata K, Kunieda M, Yamada K (2022) Simulation Of Wire EDM Combined With Measurements Of Discharge Locations And Wire Displacement. *Procedia CIRP* 113:35–40.
[217] Shoda K, Kanedo Y, Nishimura H, Kunieda M, Fan M (1992) Adaptive Control Of WEDM With On-Line Detection Of Spark Locations. In: *Proc. ISEM*, 410–416.
[218] Sirignano J, Spiliopoulos K (2018) DGM: A Deep Learning Algorithm For Solving Partial Differential Equations. *Journal of Computational Physics* 375:1339–1364.
[219] Snoeys R, Dauw D, Jennes M (1982) Survey of EDM Adaptive Control And Detection Systems. *CIRP Annals* 31(2):483–489.
[220] Snoeys R, Dekeyser W, Tricarico C (1988) Knowledge-Based System For Wire EDM. *CIRP Annals* 37(1):197–202.
[221] Speidel A, Xu D, Bisterov I, Mitchell-Smith J, Clare AT (2021) Unveiling Surfaces For Advanced Materials Characterisation With Large-Area Electrochemical Jet Machining. *Materials and Design* 202:109539.
[222] Stavropoulos P, Papacharalampopoulos A, Athanasopoulou L (2020) A Molecular Dynamics Based Digital Twin For Ultrafast Laser Material Removal Processes. *International Journal of Advanced Manufacturing Technology* 108(1):413–426.
[223] Stemmler S, Ay M, Schwenzer M, Abel D, Bergs T (2019) Model-Based Predictive Force Control In Milling. In: *Proc. 18th IEEE ECC*, 4313–4318.
[224] Steuben JC, Iliopoulos AP, Michopoulos JG (2016) Discrete Element Modeling Of Particle-Based Additive Manufacturing Processes. *Computer Methods in Applied Mechanics and Engineering* 305:537–561.
[225] Stojanovic N, Milenovic D (2018) Data-Driven Digital Twin Approach For Process Optimization: An Industry Use Case. *IEEE BigData* : 4202–4211.
[226] Stonebraker M, Çetintemel U (2018) "One Size Fits All" An Idea Whose Time Has Come And Gone. *Making Databases Work: the Pragmatic Wisdom of Michael Stonebraker*, 441–462.
[227] Streckenbach J, Koref IS, Rechenberg I, Uhlmann E (2020) Optimization With The Evolution Strategy By Example Of Electrical-Discharge Drilling. *Neurocomputing* 391:318–324.
[228] Susto GA, Schirru A, Pampuri S, McLoone S, Beghi A (2014) Machine Learning For Predictive Maintenance: A Multiple Classifier Approach. *IEEE Transactions on Industrial Informatics* 11(3):812–820.
[229] Tao F, Cheng J, Qi Q, Zhang M, Zhang H, Sui F (2018) Digital Twin-Driven Product Design, Manufacturing And Service With Big Data. *International Journal of Advanced Manufacturing Technology* 94(9):3563–3576.
[230] Tao F, Zhang M (2017) Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing. *IEEE Access* 5:20418–20427.
[231] Tarabeux J, Pateloup V, Michaud P, Chartier T (2018) Development Of A Numerical Simulation Model For Predicting The Curing Of Ceramic Systems In The Stereolithography Process. *Journal of the European Ceramic Society* 38(11):4089–4098.
[232] Tchoupe E, Heidemanns L, Küpper U, Herrig T, Klink A, Bergs T (2022) Towards In-Process Evaluation Of The Precise Electrochemical Machining (PECM). *Procedia CIRP* 113:392–397.
[233] Tourret D, Francois MM, Clarke AJ (2019) Multiscale Dendritic Needle Network Model Of Alloy Solidification With Fluid Flow. *Computation Materials Science* 162:206–227.

[234] Tseng C-C, Li C-J (2019) Numerical Investigation Of Interfacial Dynamics For The Melt Pool Of Ti-6Al-4V Powders Under A Selective Laser. *International Journal of Heat & Mass Transfer* 134:906–919.
[235] Uhlemann TH-J, Lehmann C, Steinhilper R (2017) The Digital Twin: Realizing The Cyber-Physical Production System For Industry 4.0. *Procedia CIRP* 61:335–340.
[236] van der Velden T, Rommes B, Klink A, Reese S, Waimann J (2021) A Novel Approach For The Efficient Modeling Of Material Dissolution In Electrochemical Machining. *International Journal of Solids and Structures* 229:111106.
[237] Verhaeghe F, Craeghs T, Heulens J, Pandelaers L (2009) A Pragmatic Model For Selective Laser Melting With Evaporation. *Acta Materialia* 57(20):6006–6012.
[238] Wang C-P, Erkorkmaz K, McPhee J, Engin S (2020) In-Process Digital Twin Estimation For High-Performance Machine Tools With Coupled Multibody Dynamics. *CIRP Annals* 69(1):321–324.
[239] Wang J, Sun Y, Zhang W, Thomas I, Duan S, Shi Y (2016) Large-Scale Online Multitask Learning And Decision Making For Flexible Manufacturing. *IEEE Transactions on Industrial Informatics* 12(6):2139–2147.
[240] Wang J, Xu Z, Wang J, Zhu D (2021) Electrochemical Machining On Blisk Channels With A Variable Feed Rate Mode. *Chinese Journal of Aeronautics* 34 (6):151–161.
[241] Wang P, Liu Z, Gao RX, Guo Y (2019) Heterogeneous Data-Driven Hybrid Machine Learning For Tool Condition Prognosis. *CIRP Annals* 68(1):455–458.
[242] Wang X, Lin J, Patel N, Braun M (2016) A Self-Learning And Online Algorithm For Time Series Anomaly Detection, With Application in CPU Manufacturing. In: *Proc. CIKM'16*, 1823–1832.
[243] Wang Z, Yan W, Liu WK, Liu M (2019) Powder-Scale Multi-Physics Modeling Of Multi-Layer Multi-Track Selective Laser Melting With Sharp Interface Capturing Method. *Computational Mechanics* 63(4):649–661.
[244] Wei H, Mazumder J, DebRoy T (2015) Evolution Of Solidification Texture During Additive Manufacturing. *Scientific Reports* 5(1):1–7.
[245] Weiner M (2016) *Simulations Are A Key Technology In The Aviation Industry*, MTU AeroReport. https://aeroreport.de/en/innovation/simulations-are-a-key-technology-in-the-aviation-industry, accessed on October 23, 2022.
[246] Wienand T, Meichsner G, Hackert-Oschätzchen M (2021) Jet Electrochemical Machining Simulation Of Intersecting Line Removals With Adjustable Nozzle Diameter By A Finite Area Element Grid. *Procedia CIRP* 102:349–354.
[247] Wienand T, Meichsner G, Hackert-Oschätzchen M (2020) Transient Removal Simulation Of The Jet Electrochemical Machining Process Based On A Finite Area Element Grid. In: *Proc. 16th INSECT*, 105–116.
[248] Willcox K, Peraire J (2002) Balanced Model Reduction Via The Proper Orthogonal Decomposition. *AIAA Journal* 40(11):2323–2330.
[249] Wu M, Arshad MH, Saxena KK, Qian J, Reynaerts D (2021) Data-Driven Framework Of ECM: A Machine Learning Model For Profile Prediction. In: *Proc. 17th INSECT*, 231–240.
[250] Wu S, Lei Z, Jiang M, Liang J, Li B, Chen Y (2022) Experimental Investigation And Discrete Element Modeling For Particle-Scale Powder Spreading Dynamics InPowder-Bed-Fusion-Based Additive Manufacturing. *Powder Technology* 403: 117390.
[251] Wu Y-C, San C-H, Chang C-H, Lin H-J, Marwan R, Baba S, Hwang W-S (2018) Numerical Modeling Of Melt-Pool Behavior In Selective Laser Melting With Random Powder Distribution And Experimental Validation. *Journal of Materials Processing Technology* 254:72–78.
[252] Xia H, Kunieda M, Nishiwaki N (1999) Simulation Of Electrode Surface Temperature In Die-Sinking EDM Process. *International Journal of Electrical Machines & Drives* 4:13–18.
[253] Xia H, Kunieda M, Nishiwakp N, Lior N (1994) Measurement Of Energy Distribution Into Electrodes In EDM Processes. in Usui E, (Ed.) *Advancement of Intelligent Production*, Elsevier, Amsterdam, 601–606.
[254] Yang J, Yue H, Mirihanage W, Bartolo PJ (2023) Multi-Stage Thermal Modelling Of Extrusion-Based Polymer Additive Manufacturing. *Polymers* 15(4):838.
[255] Yang T, Yao S, Xue K (2019) Slicing Point Cloud Incrementally For Additive Manufacturing Via Online Learning. *Neural Computing and Applications* : 1–21.
[256] Yi L, Glatt M, Ehmsen S, Duan W, Aurich JC (2021) Process Monitoring Of Economic And Environmental Performance Of A Material Extrusion Printer Using An Augmented Reality-Based Digital Twin. *Additive Manufacturing* 48:102388.
[257] Yoshino H, Kunieda M (1995) Sensitivity Analysis In Edm Spark Location Measurement By Branched Electric Current Method. *Journal of the Japan Society for Precision Engineering* 61(5):682–686.
[258] Yuan MG, Ueda Y (1996) Prediction Of Residual Stresses In Welded T-And I-Joints Using Inherent StraIns. *Journal of Engineering Materials and Technology* 118(2):229–234.
[259] Zäh MF, Lutzmann S (2010) Modelling And Simulation Of Electron Beam Melting. *Production Engineering* 4(1):15–23.
[260] Zahiruddin M, Kunieda M (2016) Analysis of Micro Fin Deformation Due To Micro EDM. *Procedia CIRP* 42:569–574.
[261] Zambrano V, Mueller-Roemer J, Sandberg M, Talasila P, Zanin D, Larsen PG, Loeschner E, Thronicke W, Pietraroia D, Landolfi G (2022) Industrial Digitalization In The Industry 4.0 Era: Classification, Reuse And Authoring Of Digital Models On Digital Twin Platforms. *Array* 14:100176.
[262] Zambrano V, Rodríguez-Barrachina R, Calvo S, Izquierdo S (2020) TWINKLE: A Digital-Twin-Building Kernel For Real-Time Computer-Aided Engineering. *SoftwareX* 11:100419.
[263] Zanjani MY, Hackert-Oschätzchen M, Martin A, Schubert IA (2017) Evaluation Of On-Machine Gap Measurement Strategies In Jet-Electrochemical Machining. In: *Proc. 13th INSECT*, 94–100.
[264] Zanjani Y, Martin A, Zinecker M, Schubert A (2020) Statistical Analysis Of Jet Electrochemical Post-Processing Of Additively Manufactured Workpieces. In: *Proc. 16th INSECT*, 77–84.
[265] Zeis M (2017) Deformation Of Thin Graphite Electrodes With High Aspect Ratio During Sinking Electrical Discharge Machining. *CIRP Annals* 66 (1):185–188.
[266] Zeis M, Fritzke S, Redich H, Feiling N, Niegl M (2018) Quality And Cost Improvements In Precise Electrochemical Machining Through Process Data Management. In: *Proc. 14th INSECT*, 81–86.
[267] Zhao J, Han M, Li L (2021) Modeling And Characterization Of Shape Memory Properties And Decays For 4D Printed Parts Using Stereolithography. *Materials and Design* 203:109617.
[268] Zhao P, He Y, Trindade GF, Baumers M, Irvine DJ, Hague RJ, Ashcroft IA, Wildman RD (2021) Modelling The Influence Of UV Curing Strategies For Optimisation Of Inkjet Based 3D Printing. *Materials and Design* 208:109889.
[269] Zheng M, Wei L, Chen J, Zhang Q, Li J, Sui S, Wang G, Huang W (2019) Surface Morphology Evolution During Pulsed Selective Laser Melting: Numerical And Experimental Investigations. *Applied Surface Science* 496.
[270] Zheng M, Wei L, Chen J, Zhang Q, Li J, Sui S, Wang G, Huang W (2019) Surface Morphology Evolution During Pulsed Selective Laser Melting: Numerical And Experimental Investigations. *Applied Surface Science* 496:143649.
[271] Zohdi TI (2014) Additive Particle Deposition And Selective Laser Processing-A Computational Manufacturing Framework. *Computational Mechanics* 54 (1):171–191.

Please cite this article as: Y. Guo et al., Digital twins for electro-physical, chemical, and photonic processes, CIRP Annals - Manufacturing Technology (2023), https://doi.org/10.1016/j.cirp.2023.05.007