(Article begins on next page)

Digital Twin Applications in the Energy Sector

Saeid Shahmoradi
Dip. Energia "Galileo Ferraris"
Politecnico di Torino
Torino, Italy
saeid.shahmoradi@polito.it

Andrea Mazza
Dip. Energia "Galileo Ferraris"
Politecnico di Torino
Torino, Italy
andrea.mazza@polito.it

Enrico Pons
Dip. Energia "Galileo Ferraris"
Politecnico di Torino
Torino, Italy
enrico.pons@polito.it

***Abstract*—Recently, there has been a significant interest in the integration of engineering systems into digital formats. This trend has attracted considerable attention because of the numerous advantages it offers in terms of enhancing system performance and reducing costs. Within digitalization techniques, one approach that has gained prominence is the utilization of Digital Twins (DTs). DTs have emerged as a promising method for improving performance, reducing maintenance and operation expenses, and ensuring the safety of associated systems. This research provides an in-depth analysis of the key concepts and characteristics of existing studies on DTs applied in diverse energy systems areas. This study also illustrates the wide range of application areas where DT technology can be employed in power systems such as battery management systems, power monitoring systems, microgrid management, fault detection, and demand forecasting. Furthermore, the research aims to provide insights into future research directions that can facilitate the practical implementation of DTs in various domains.**

***Index Terms*—Digital twin, Energy sector, Structure, Renewable energy**

I. Introduction

Power systems have become complicated and constantly changing mainly because of Renewable Energy Sources (RESs) penetration [19]. This is one of the primary reasons driving researchers to address electricity market deregulation and the use of energy resources. Future of power systems will experience an increased level of complexity due to numerous factors influencing different levels of the system, with a particular emphasis on the distribution system [12]. There are numerous local distribution systems managed by distribution suppliers (operators), in addition to consumers and other entities involved. As a result, power flows are no longer exclusively unidirectional and do not move solely from the centralized power system to the final consumer. Instead, the tracking of power flow becomes increasingly complex, as it can occur between consumers, consumers and the grid, the grid and consumers, and some of these flows may be intermittent or unpredictable. With increasing complexity in systems and components being developed for new technologies that aim to target net-zero emissions, maintenance and operation cost of the system can increase [10]. Due to this, systems representing new technologies will be difficult to sell to potential customers, and every industry will need to adapt in a new way to address this challenge. For example, reducing global greenhouse gas emissions will be driven by complex new energy systems that will inherently be more integrated and highly dynamic in nature. These highly integrated energy systems of the future will also have an impact on system operation and maintenance costs that would require state-of-the-art control and monitoring systems [20]. Machine Learning (ML) is an integral part in the development and operation of DTs [2], ML techniques can be used to develop data-driven models that capture the behavior and dynamics of the physical system, in addition, by training ML models on sensor data from the physical system, DTs can detect anomalies and predict failures or maintenance needs. Not only that, but also ML algorithms will continuously analyze sensor data from the physical system and provide real-time monitoring and decision support [17].

A DT can be described as a computer-based replica that mimics the characteristics, proportions, and likelihoods of either a system or real object by incorporating data from multiple origins, which operates to imitate the actions and performance of the physical object. DTs gained popularity in various fields after their introduction [3], inclusive of

- Healthcare; they simulate patient data, treatment processes, and facility operations, facilitating personalized care and operational optimization.
- Transportation; it is possible to simulate vehicles, infrastructure, and traffic flow, enabling predictive analytics for route optimization and traffic management [6].
- Maritime; it is feasible to optimize vessel performance, fuel consumption, and route planning, enhancing efficiency and reducing environmental impact. Digital twins simulate maintenance needs, preventing unexpected downtime and ensuring safety compliance [7].
- Manufacturing; Digital twins can not only simulate different production scenarios, enabling real-time adjustments to improve efficiency and minimize downtime, but also optimize production schedules, predict equipment failures, and enhance quality control [9].
- Re-manufacturing; DT is able to facilitate efficient refurbishment and reuse of products [4].
- Aerospace; DTs contribute to simulating flight conditions, creating virtual replicas of aircraft and performance, facil-

This publication is part of the project PNRR-NGEU which has received funding from the MUR - DM 117/2023.

Funded by the European Union
Ministero dell'Università e della Ricerca
Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA

itating predictive maintenance and safety enhancements [5].

This article provides an overview of the possible DT structures and applications and analyze new trend papers that discuss incorporation of this new technology, DT, within energy sector.

The following outline shows the structure of this paper: Section II provides numerous DT definitions currently gaining dominance in literature, compares and combines, and introduces a novel and widely applicable definition. Section III describes approaches employed for conducting the systematic literature review methodology, in particular, focusing on DT within energy sector. In Section IV, the results of this review can be found with an emphasis on applications and methods of DT within energy sector. Based on the review results, Section V concludes the article.

II. What is Digital Twin?

This study aims to discuss the application of DT to the energy sector. In this regard, the main research questions are:

- How is DT defined in both the academic and industrial areas?
- What are the main DT structures?
- What approaches, techniques, frameworks and algorithms, have been used in DTs?
- What is the main focus of future work on DT within energy sector?

A. Definition

In [15] DT is introduced as a virtual depiction of a physical (real world) system, being constantly updated by real-time information regarding health, performance, and maintenance of whole life cycle of physical entity. The Authors in [23] defined DT as a model where specific online measurements can be incorporated progressively into a simulation environment, along with active simulation model influencing real-world adjustments in an adaptive manner. In [14] instead the DT is defined as a virtual entity or a collection of virtual entities in a virtual (digital) space, illustrating a mapping correlation with real world within physical space. Industry definitions from companies like Siemens, Microsoft, and Emerson adapted their language to emphasize the unique capabilities of their DT platforms, rather than presenting a generic definition. Microsoft introduced Microsoft Azure DTs which is an Internet of Thing (IoT)-enabled platform which offers the capability to integrate both worlds, physical and digital. Emerson introduced a DT starter package which suggested in 2019 declares to be initial steps toward establishing a DT for a production facility in industry. It offers a digital duplicate of control system, which emulates operations without intruding. Siemens defined DT as the exact virtual representation of product or manufacturing plant.

Many of the definitions found in literature suffer from a weakness that is they follow a specific DT focusing for single target or application, which does not translate effectively to other contexts. Simultaneously, there's a necessity to differentiate between the various types and levels of fidelity in DT representations. To cope with the challenges, [28] uses broad terminology to define and cluster DTs across a diverse array of applications.

B. History of Digital Twin: Development and conception

The concept of DT has been evolving over the past years and experiencing numerous definitions in the literature, leading to a lack of consistency not only within the research domain but also for industrial applications [18]. From 1970, NASA faced a problem with the Apollo 13 spacecraft and used simulations to test various maintenance scenarios. By utilization of digital simulation for a physical component, researchers were able to detect optimal course of action for spacecraft repairs, leading to safe and secure return of astronauts. In 2003, thirty years after the initial occurrence, Grieves [8] introduced the phrase "digital twin" to characterize an entity or system consisting of a physical component, a digital or virtual copy as well as a linkage connecting between them. Grieves expanded the definition of DT to encompass a DT instance, a DT prototype, and an aggregate. Recognizing the parallels along with the crisis of 1970 mission, NASA adopted the concept of a DT for its implementation on spacecrafts during 2010 [21] and 2011 [24]. Following Grieves' contribution, the majority of papers characterized DT portrayed as a high-precision simulation, lacking a clear link between the physical and digital components. As DT research progressed, an increasing number of researchers focused their attention on the relationship between components, both virtual and physical. Moreover, exploration into idea of self-adaptation within DTs has started to be investigated, introducing methods like adeptness and self-evolution [22], [25].

Since the year 2010, research activity in DT area has seen a remarkable increase, expanding into new domains such as sustainable and renewable energy resources. Figure 1 presents a representation of advancements and developments in DT over time, highlighting the evolution of its definitions and development emphasising. Specifically, two studies played a crucial role in definition and clarifying distinct kinds of DTs. Kritzinger et al [11]. introduced a classification of DT definition, dividing it into three different classes based on the degree of data merging (ranging from most to least): DT, digital shadow as well as digital model. The linkage between physical as well as digital sections was identified as a distinguishing feature. Consequently, based on Kritzinger et al. a digital model only encompasses nonautomated [25] data flow between digital and physical components; a digital shadow is characterized by an unidirectional automated flow of data while DT necessitates a bidirectional automated exchange of data. comprehensive classification of DT modeling in general.

III. typical DT structures

Madni et al. [15] suggested the classifying of DT into five clusters: 1) level of model complexity 2) existence of physical

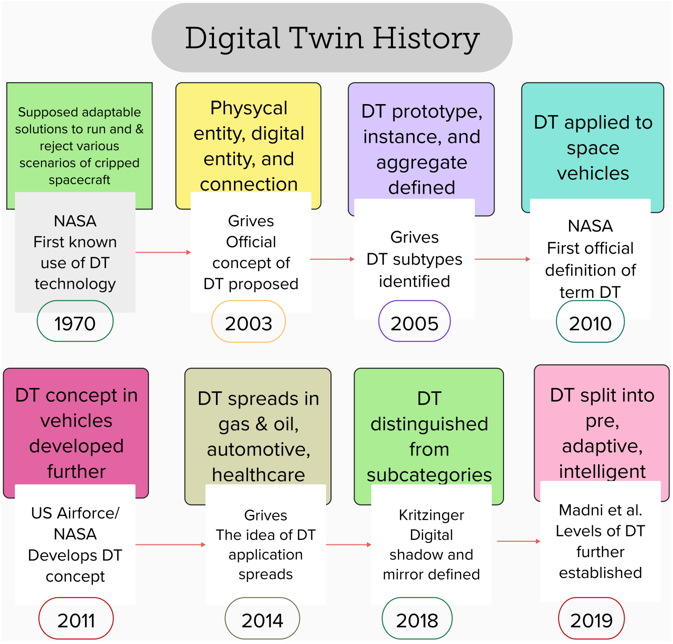

Fig. 1. Digital Twin Developments: Brief History

component 3) data gathering from physical component 4) learning the preferences of operators through machine learning and finally 5) system and environment's machine learning. This review paper concentrates on literature which applies and discusses DT in energy sector technology. This part summarizes review methods and recently-published studies for energy industry emphasizing on DT in publications from the energy sector to detect gaps in this field. The suggested generic framework for classifying DTs is utilized to extract the core characteristics of existing research applications. This information can assist other researchers in addressing future requirements within the energy sector. Initially, we defined the focus of our study as "DT applications in power systems and the energy sector". Within this specified scope, we formulated our research question as follows: "What are the advantages of employing DT within energy sector?" As previously mentioned, we conducted search on web engines using a variety of relevant keywords. Although there are lots of applications of DT in industries, our primary objective was on power system.

To be assured the chosen papers can meet requirements of this work, the selected papers adhered to these criteria:

- Only papers written in English.
- Published between the years 2018–2024.
- Must concentrate on DT concepts, key technological breakthroughs, and energy sector.
- Do not be a repetitive paper (sometimes internet search tools may produce repetitive links to same piece of work).

According to the final results, the outcomes are classified based on the common structures employed in papers. Figure 2 illustrates a general view of data-flow between different components of DTs including: **Physical space**; The real-world item being modeled, such as a machine, building, or process. **Digital space**; The virtual representation of the physical entity, often created using CAD models, 3D simulations, or other digital design tools. **Connection**; The communication infrastructure that enables data transfer between the physical entity and the digital model. **Data**; Real-time and historical data collected from sensors and other sources on the physical entity, which inform the digital model.

IV. Results

In the field of power systems, according to the available models and approaches, DT technology is able to be incorporated into the power system for diverse objectives such as optimizing power grid design, simulating faults in power grid, developing virtual facilities in terms of power plants, monitoring intelligent equipment as well as providing other related services [1]. However, the authors primarily focus on structures utilized in DTs instead of applications, they are outlined in table I. It is worth noting that references are only examples to discuss deeper about the different aspects of the structures.

A. Physical-based DT

This structure mainly relies on detailed physical and mathematical models to simulate the behavior and performance of a physical system. In [16] PEMFC, a system for overseeing health and prognostics conditions of system to anticipate an important item, system useful lifetime, a denoising auto encoder was additionally employed to simulate the Remaining Useful Life (RUL) of the cells based on the voltage stack values in the physical domain. A DT prognostics method is introduced for predicting the RUL of PEMFCs. The digital side of the PEMFC is modeled, stacked autoencoders are utilized to capture the degradation behavior of the PEMFC. The proposed DT prognostics method is divided into two main phases:

- Modeling Phase: An offline phase where a model is built to mirror the behavior of the PEMFCs using historical data and transfer learning is used here to train the DT model with historical data.
- Updating Phase: An online phase where the DT model is updated using real-time data collected from sensors, as well as, a deep transfer learning model based on stacked denoising autoencoders is utilized to continuously update the DT with online measurements.

The method achieves high prediction accuracy even with limited measurement data, the use of transfer learning allows the model to adapt to new data and conditions. The weaknesses of this structure could be seen as the implementation of such a DT system can be complex and may require significant computational resources, the accuracy of the model depends heavily on the availability of quality and quantity of the historical and real-time data. The paper does dive deeply into a purely physical-based structure for the digital twin with physical knowledge. The key components related to the physical aspect include:

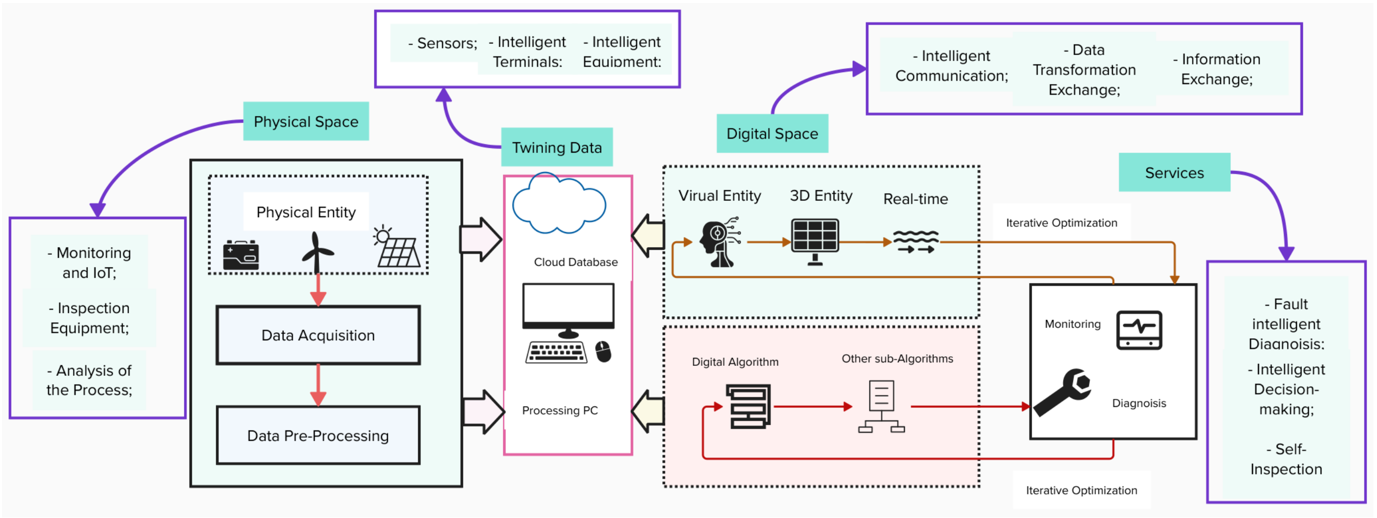

Fig. 2. Common structure and data flow in Digital Twins

TABLE I
RESULTS OF SEARCH IN VARIOUS SOURCES IN ENERGY SECTOR

N.	Ref.	DT Structure	Physical Space	Digital Space	Weakness	ICT Layer	Strength
1	[16]	Data-Driven	A proton exchange membrane fuel cell (PEMFC) system for managing the prognostics and health states of the system to predict the system's useful lifetime	A PEMFC system (Dynamic simulation of hydrogen fuel cell systems)	Limited flexibility to adapt to changes in operational conditions	The stacked denoising autoencoder was also utilized to model the cells' remaining useful life from the physical space voltage stack values	Accurate replication of physical system dynamics
2	[13]	Physical-Based	DT of the medium voltage (MV) sides of distribution transformer based on low voltage (LV) side	Extended Thevenin model, employed for real-time estimation of the battery's status	High dependency on quality and quantity of data	Enables proactive energy management and improves grid stability	High accuracy in fault detection due to robust data analytics
3	[26]	Hybrid	A DC power source, a battery test system and battery pack and a temperature chamber are used for battery aging tests and charge/discharge tests	The Battery Management System (BMS) master and slave modules are used for algorithm operation and data acquisition. The 5G data transmission module and aerials are used to transmit data to the host computer	Implementation complexity and high computational requirements	cloud-side-end BMS and a four-layer networked architecture of cloud-side-end collaboration for BMS	Combines physical models with real-time data, enhancing predictive capabilities
4	[27]	Adaptive	Real Li-ion BMS	data management and model management modules are needed to process and manage the data and provide all the needed models to estimate the remaining useful life-cycle, degradation, and reliability of the system	Complexity in model adaptation and evolution, potentially high computational load	sensors data acquisition, including design data, operation data, real-time feedback data	Adaptive and evolving model improves accuracy over time, enhanced prediction of battery life and performance

- PEMFC System: The physical part of the DT, consisting of the PEMFC stack and its auxiliaries.
- Sensors: Essential for collecting real-time data from the PEMFC system, which is then used to update the digital model.
- Historical Data: Used to initially train the DT model, incorporating the degradation patterns and operational profiles of the PEMFC.

B. Data-driven DT

This structure utilize large amounts of collected data from sensors and other sources to create models and insights about the physical system. In [13] a cloud-based BMS that leverages a digital twin framework is discussed. Batteries are the primary source of data, representing the physical batteries (either lithium-ion or lead-acid) whose State of Charge (SoC) and State of Health (SoH) need to be monitored. They provide real-time data on voltage, current, temperature, and other relevant parameters. The paper emphasizes the use of data-driven approaches for both SoC and SoH estimation. This involves:

- Data Collection: Continuous measurement of relevant battery parameters (voltage, current, temperature) via sensors.
- Data Transmission: Seamless and real-time transmission of collected data to the cloud using IoT components.
- Data Storage: Storing vast amounts of data on the cloud platform for historical analysis and algorithm training.

BMS-slave section is acting as the data acquisition unit within the BMS. This section has two different components including: Multi-cell Battery Monitors which are used to monitor the individual cells in a battery pack and Microcontrollers That process the acquired data from the sensors. They are responsible for sensing and collecting data from the battery cells, performing signal acquisition and filtering.

IoT component facilitates seamless data transmission from the Battery Management System (BMS)-slave to the cloud platform which Wi-Fi, Bluetooth, or other wireless communication technologies are an integral part of the system. Application Programming Interface (API) and User Interface (UI) will facilitates data access and manipulation for external applications and services, additionally, provide a visual representation of the battery status, diagnostic results, and allows for monitoring and control of the battery systems, respectively. Strengths of this structure are as following: The cloud platform significantly enhances computational capabilities, allowing for more complex and accurate algorithms. Improved SoC and SoH estimation algorithms provide more reliable and accurate battery monitoring and wireless IoT communication enhances system reliability by reducing wiring complexity.

Weaknesses can be considered as real-time operation relies heavily on stable internet connections, which might be a limitation in certain scenarios and implementing cloud infrastructure and maintaining it is costly, particularly for small-scale applications.

C. Hybrid DT

This structure combines both physical-based models and data-driven approaches to leverage the strengths of both methods. In [26] a new architecture is introduced for BMS to leverage cloud computing and overcome limitations in computing capacity and storage, additionally, a hybrid structure that integrates: 1) Real-Time Data Collection; Using IoT sensors and 5G transceiver modules to gather real-time data from batteries. 2) Virtual Simulation; Creating a virtual model that mirrors the physical battery's behavior. 3) Two-Way Dynamic Mapping; Ensuring continuous data flow between the physical battery and its digital twin for real-time updates and adjustments. 4) Online Learning and Model Updating; Employing machine learning to update the digital twin model dynamically based on incoming data.

The hybrid structure proposed in this paper is a four-layer networked architecture consisting of:

- Cloud Layer: Utilizes cloud servers for large-scale data storage and computation and implements advanced analytics and machine learning to process battery data and provide insights
- Side Layer (Edge Computing): Performs preliminary data processing and filtering closer to the data source and reduces latency by handling time-sensitive operations locally before sending data to the cloud.
- End Layer (Local Devices): Employs IoT devices and sensors to collect real-time data from the battery systems and executes immediate control actions based on local data analysis.
- Network Layer: Ensures seamless data transmission between the end devices, edge nodes, and cloud servers and utilizes 5G technology for fast and reliable communication.

D. Adaptive DT

Adaptive structure is capable of evolving and updating itself over time based on new data and changing conditions. In [27] the adaptive structure is centered around the Model Evolution Module, which ensures that the DT remains accurate over time by continuously updating its models. Key components include:

- Historical and Real-time Data Integration: Combines past and current data to refine model predictions.
- Bayesian Regression: Used for updating model parameters based on new data.
- Neural Networks: Employed for capturing complex, non-linear relationships within the data.
- Maximum Likelihood Parameter Estimation: Helps in accurately estimating model parameters.

In this structure Data Acquisition Module collects data such as design, operation, and real-time feedback data to send them to Data Management Module. This module processes and manages various data types including basic data, algorithm and model data, expert knowledge, and derived data. Model Management Module stores, uses, manages, and updates all models. Simulation and Calculation Module integrates various algorithms to facilitate description, prediction, diagnosis, analysis procedure. In the next step, Model Evolution Module, updates and evolves the DT models using historical and real-time data. Finally, Visualization Module visualizes DT models, and provides human–computer interaction interfaces.

Combination of real-time and historical data for accurate life prediction, usage of Bayesian algorithms to adaptively evolve models, improving prediction accuracy, and coverage of data acquisition, management, modeling, simulation, visualization, and maintenance decision-making are strengths of this structure. Weaknesses could be addressed in complexity of implementation of this structure.

V. Conclusion

The current power systems have become complicated and constantly changing because of RES penetration, nonlinear loads, electric vehicles (EVs), and charging stations. Consequently, there is a huge amount of data generated in these systems. Hence, it is crucial to recognize that a potential technical challenge in conducting effective research lies in accessibility of high-speed monitoring. The issue can be solved through collaborating with a suitable partner which has access to an advanced network capable of facilitating high-speed data communication which DT technology could provide this structure. This work reviews the application of DT technology in the field of energy such as BMS, Power Monitoring System (PMS), microgrid management, fault detection, and demand forecasting and focuses deeply on the common structures employed within this field.

References

[1] Ali Aghazadeh Ardebili, Antonella Longo, Antonio Ficarella, et al. Digital twin (dt) in smart energy systems-systematic literature review of dt as a growing solution for energy internet of the things (eiot). In *E3S Web of Conferences*, volume 312, pages 1–18, 2021.

[2] Bahar Biller and Stephan Biller. Implementing digital twins that learn: Ai and simulation are at the core. *Machines*, 11(4), 2023.

[3] José Antônio de Queiroz Rafael de Carvalho Miranda Carlos Henrique dos Santos, José Arnaldo Barra Montevechi and Fabiano Leal. Decision support in productive processes through des and abs in the digital twin era: a systematic literature review. *International Journal of Production Research*, 60(8):2662–2681, 2022.

[4] Ziyue Chen and Lizhen Huang. Digital twin in circular economy: Remanufacturing in construction. In *IOP Conference Series: Earth and Environmental Science*, volume 588, page 032014. IOP Publishing, 2020.

[5] James Domone. Digital twin for life predictions in civil aerospace. *Atkins White Paper. Digital twin can potentially integrate all the data between previous generation vehicles and current vehicle concept in its digital model*, 2018.

[6] Yan Gao, Shuyue Qian, Zihan Li, Ping Wang, Feiyue Wang, and Qing He. Digital twin and its application in transportation infrastructure. In *2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI)*, pages 298–301, 2021.

[7] Jan-Erik Giering and Alexander Dyck. Maritime digital twin architecture. *at - Automatisierungstechnik*, 69(12):1081–1095, 2021.

[8] Michael Grieves. Digital twin: Manufacturing excellence through virtual factory replication. 03 2015.

[9] Zhi Li Kai Ding Guanghui Zhou, Chao Zhang and Chuang Wang. Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing. *International Journal of Production Research*, 58(4):1034–1051, 2020.

[10] Leila Kamyabi, Tek Tjing Lie, and Samaneh Madanian. Applications of digital twins in power systems: A perspective. *Transactions on Energy Systems and Engineering Applications*, 3(2):1–9, Nov. 2022.

[11] Werner Kritzinger, Matthias Karner, Georg Traar, Jan Henjes, and Wilfried Sihn. Digital twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, 51(11):1016–1022, 2018. 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018.

[12] Hongcheng Li, Dan Yang, Huajun Cao, Weiwei Ge, Erheng Chen, Xuanhao Wen, and Chongbo Li. Data-driven hybrid petri-net based energy consumption behaviour modelling for digital twin of energy-efficient manufacturing system. *Energy*, 239:122178, 2022.

[13] Weihan Li, Monika Rentemeister, Julia Badeda, Dominik Jöst, Dominik Schulte, and Dirk Uwe Sauer. Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation. *Journal of Energy Storage*, 30:101557, 2020.

[14] Qing Liu, Bin Liu, Guan Wang, and Chen Zhang. A comparative study on digital twin models. *AIP Conference Proceedings*, 2073(1):020091, 02 2019.

[15] Azad M. Madni, Carla C. Madni, and Scott D. Lucero. Leveraging digital twin technology in model-based systems engineering. *Systems*, 7(1), 2019.

[16] Safa Meraghni, Labib Sadek Terrissa, Meiling Yue, Jian Ma, Samir Jemei, and Noureddine Zerhouni. A data-driven digital-twin prognostics method for proton exchange membrane fuel cell remaining useful life prediction. *International Journal of Hydrogen Energy*, 46(2):2555–2564, 2021.

[17] Matteo Perno, Lars Hvam, and Anders Haug. A machine learning digital twin approach for critical process parameter prediction in a catalyst manufacturing line. *Computers in Industry*, 151:103987, 2023.

[18] Ferguson S. Apollo 13: the first digital twin. Accessed: 13 June 2021.

[19] Benjamin Schleich, Nabil Anwer, Luc Mathieu, and Sandro Wartzack. Shaping the digital twin for design and production engineering. *CIRP Annals*, 66(1):141–144, 2017.

[20] Concetta Semeraro, A.G. Olabi, Haya Aljaghoub, Abdul Hai Alami, Muaz Al Radi, Michele Dassisti, and Mohammad Ali Abdelkareem. Digital twin application in energy storage: Trends and challenges. *Journal of Energy Storage*, 58:106347, 2023.

[21] Mike Shafto, Mike Conroy, Rich Doyle, Ed Glaessgen, Chris Kemp, Jacqueline LeMoigne, and Lui Wang. Draft modeling, simulation, information technology & processing roadmap. *Technology area*, 11:1–32, 2010.

[22] Fei Tao, Jiangfeng Cheng, Qinglin Qi, Meng Zhang, He Zhang, and Fangyuan Sui. Digital twin-driven product design, manufacturing and service with big data. *The International Journal of Advanced Manufacturing Technology*, 94(9):3563–3576, Feb 2018.

[23] Qi Qinglin Zhang Meng Zhang He Sui Fangyuan Tao Fei, Cheng Jiangfeng. Digital twin-driven product design, manufacturing and service with big data. *The International Journal of Advanced Manufacturing Technology*, 94(1), 2018.

[24] Eric J. Tuegel, Anthony R. Ingraffea, Thomas G. Eason, and S. Michael Spottswood. Reengineering aircraft structural life prediction using a digital twin. *International Journal of Aerospace Engineering*, 2011(1):154798, 2011.

[25] Peng Wang, Mei Yang, Yong Peng, Jiancheng Zhu, Rusheng Ju, and Quanjun Yin. Sensor control in anti-submarine warfare—a digital twin and random finite sets based approach. *Entropy*, 21(8), 2019.

[26] Yujie Wang, Ruilong Xu, Caijie Zhou, Xu Kang, and Zonghai Chen. Digital twin and cloud-side-end collaboration for intelligent battery management system. *Journal of Manufacturing Systems*, 62:124–134, 2022.

[27] Dezhen Yang, Yidan Cui, Quan Xia, Fusheng Jiang, Yi Ren, Bo Sun, Qiang Feng, Zili Wang, and Chao Yang. A digital twin-driven life prediction method of lithium-ion batteries based on adaptive model evolution. *Materials*, 15(9), 2022.

[28] Wei Yu, Panos Patros, Brent Young, Elsa Klinac, and Timothy Gordon Walmsley. Energy digital twin technology for industrial energy management: Classification, challenges and future. *Renewable and Sustainable Energy Reviews*, 161:112407, 2022.