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Efficiency and Enhanced Performance: Exploring Digital Twin Implementation in Power Plants

Concetta Semeraro [1,2,*], Haya Aljaghoub [1], Ayman Housni Ibrahim Mdallal [1], Mohammad Ali Abdelkareem [1] and Abdul Ghani Olabi [1]

[1] Sustainable Energy & Power Systems Research Centre, RISE, University of Sharjah, Sharjah P.O. Box 27272, United Arab Emirates
[2] Department of Industrial and Management Engineering, University of Sharjah, Sharjah P.O. Box 27272, United Arab Emirates
* Correspondence: csemeraro@sharjah.ac.ae

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Abstract: The utilization of digital twin technology in large-scale power plants has recently attracted considerable attention. This is because a digital twin can be an opportunity to improve multiple aspects of power plant operations, such as performance monitoring, predictive maintenance, and fault diagnosis. As a result, this study aims to present a comprehensive survey of the existing literature on applying digital twins in large-scale power plants. These applications include thermal, nuclear, and hydropower plants. Furthermore, this paper explores the distinct architecture of a large-scale power plant digital twin. This comprehensive survey paves the way for accurately identifying gaps and constraints restraining the use of digital twins for large-scale power plants. There is a clear indication of a research gap when examining the challenges and practical considerations in implementing digital twins in large-scale power plants.

Keywords: digital twin; large-scale power plants; thermal power plants; nuclear power plants; hydropower plants; energy systems architecture

1. Introduction

The current process of digitalizing organizations requires developing and implementing digital models, often known as digital twins, which encompass a thorough understanding of real operational processes [1].

Digital twins rely on the creation of virtual models that are identical to their corresponding physical entities. These models are designed to accurately replicate the states and behaviors of their physical counterparts, while also possessing the capabilities to evaluate, optimize, and anticipate outcomes. The digital twin concept includes an entire digital engineering perspective that spans several stages, including product design, development, production planning, production engineering, production, and services. Furthermore, digital twins can be developed at each step of the product life cycle to carry out various functions. Digital twin (DT) technology has undergone significant evolution. Initially introduced by Michael Grieves in 2003 and adopted by NASA in 2012 for aerospace applications [2]. In 2012, NASA defined a digital twin as an integrated, probabilistic, multi-scale, and multi-physics simulation of a system or vehicle, incorporating sensors and physical models [3]. Then, in 2017, Chen [4] defined a digital twin as a digital portrayal of a physical system that accurately represes its functional attributes and connections to its components. Liu [5] described the digital twin as a dynamic physical system model that continuously adapts to disruptions in the system's operations by utilizing real-time data. Subsequently, the digital twin employs this data to forecast the future behavior of the physical system. While these definitions convey similar concepts, they do not offer a precise and final definition of a digital twin. Consequently, in 2021, Semeraro et al. [6] introduced a conclusive definition of a DT within the manufacturing sector. They characterized the digital twin technology as a set of adaptable models that enable replicating a physical system's performance within a digital framework. The digital system obtains real-time data to simulate the physical system's behavior. Subsequently, the digital twin can anticipate future malfunctions and identify opportunities for system improvement, enabling it to recommend corrective actions. Due to the widespread use of digital twin technology, it has been developed in numerous applications for various functions. For instance, digital twins have been applied in manufacturing, remanufacturing, additive manufacturing, energy storage, renewable energy, power plants, and automotive fields. In power systems, DT adoption is driven by the urgent need for real-time system monitoring, predictive analytics, and lifecycle management. This has led to a growing interest in its deployment across thermal, nuclear, and renewable energy-based power plants [7]. Most power plant operations involve producing high-pressure superheated steam, which drives a steam turbine connected to an electric generator. Within water/steam evaporator systems, two-phase flows are commonly encountered. Due to the intricate and diverse nature of this flow pattern, numerous two-phase models with varying levels of complexity have been introduced in the literature [8]. Thermal power plants, one of the earliest forms of energy generation, are widely used today as a primary power source. The main components of a thermal power plant are the boiler, turbine, generator, condenser, cooling tower, and pump [9–11]. Even though thermal power plants have been widely utilized, they are still associated with several obstacles that negatively impact their performance and efficiency [12–14]. Challenges such as equipment aging, environmental concerns, and the need for improved efficiency have prompted thermal power plants to adopt advanced technologies such as digital technologies to address these issues. In thermal power plants, digital twin technology offers valuable support to operators by facilitating equipment monitoring, early problem detection, and overall plant efficiency improvement.

Similarly, digital twins in nuclear power plants are used to model, monitor, and optimize complex reactor systems in real time. DTs offer a virtual replica of physical assets to support predictive maintenance, and fault detection. By creating a digital twin of the power plant, operators can simulate and predict its behavior under various operating conditions. This enables them to enhance performance, prolong the plant's lifespan, and minimize downtime [6].

Hydropower is a form of renewable energy that generates electricity by using the power of water as its primary source of energy. Hydropower facilities may be found all over the globe, making it one of the oldest and most popular renewable energy sources [15,16]. Using digital twins can improve plant efficiency by simulating various situations and optimizing operational procedures, reducing energy waste and enhancing electricity generation. Moreover, digital twins can monitor equipment in real-time and detect prospective issues, empowering operators to carry out anticipated maintenance, prevent downtime, and curtail repair expenses. By simulating diverse weather scenarios, operators can ensure resilience to weather patterns, including severe droughts and heavy rainfall [17,18]. Furthermore, using digital twins can assist hydropower facilities in lessening their harmful environmental effects by replicating the impacts of their operations on water quality, wildlife, and nearby communities, and implementing strategies to mitigate these impacts [19].

There are many advantages associated with implementing digital twin technology in power plants. These benefits include increased operational efficiency and performance [20], reduced maintenance costs [21], and improved safety levels [22]. For example, operators can proactively identify potentially challenging situations and take preventive measures by simulating the plant's behaviour in a virtual environment before any actual issues arise [23]. This can significantly reduce both downtime and maintenance expenses. Additionally, plant operators can enhance the plant's efficiency, resulting in cost savings and a reduced adverse impact on the environment [24]. Figure 1 illustrates the basic functions of digital twin utilized in multiple disciplines.

This study aims to present a comprehensive review of the application of digital twins in thermal, nuclear, and hydropower plants. Examining the existing literature, the main objective is to acquire a more profound comprehension of the structures and capabilities of digital twins within the framework of smart energy systems. Furthermore, this investigation aims to demonstrate the gaps in the existing literature and pinpoint the domains that have been subject to insufficient examination, thereby highlighting the necessity for additional inquiry. This study aims to contribute value to the progress of digital twin implementations within the power generation sector.

The specific objectives of this paper are defined as follows:

1. Provides a comparative review of DT applications in thermal, nuclear, and hydropower sectors.
2. Introduces architectural and functional distinctions in DT deployment across different plant types.
3. Recommends gaps and research directions for future development.

The paper is organized as follows: Section 1 explores the application of digital twins across thermal, nuclear, and hydropower plants. Section 2 presents the architectural layers and operational structure of digital twin systems.

Section 3 highlights implementation challenges and current research gaps and concludes with key findings and directions for future research.

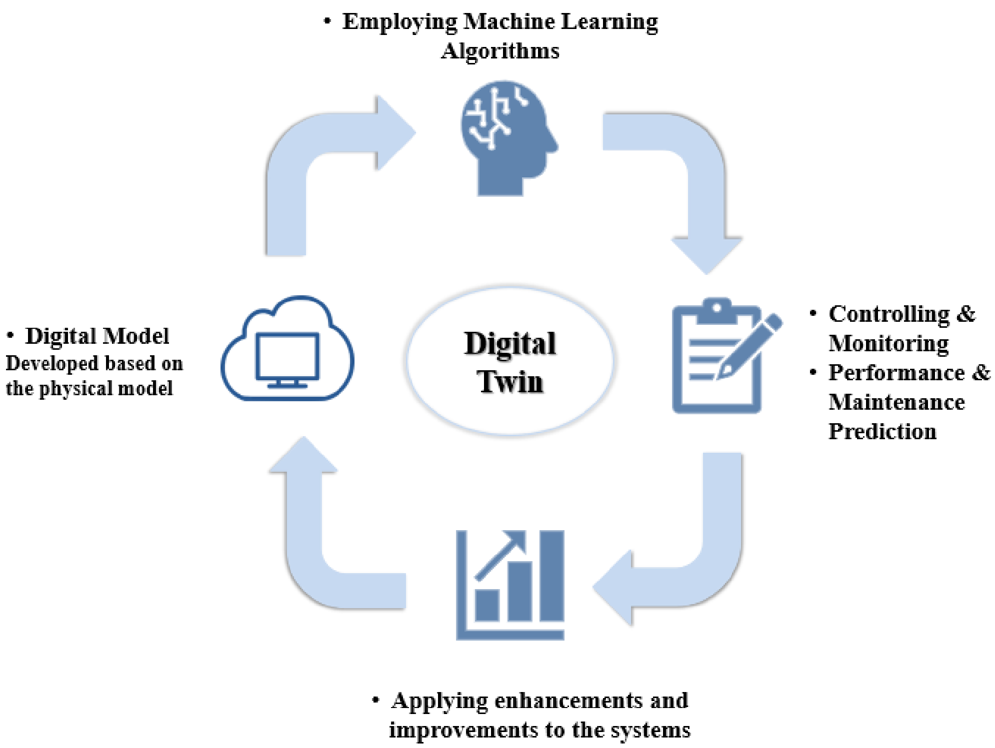
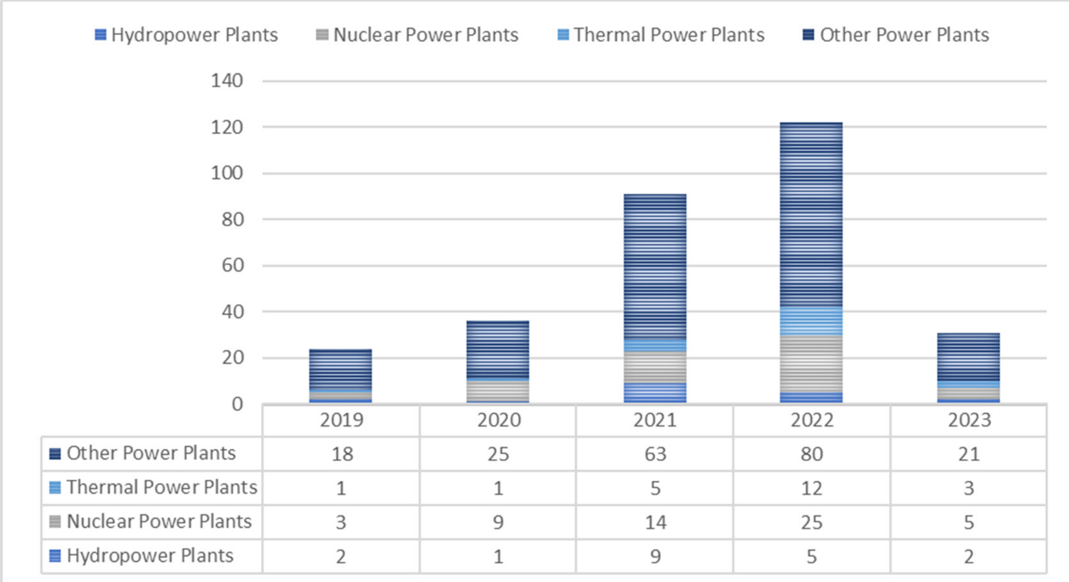


Figure 1. Basic functions of the digital twin.

2. Applications of Digital Twin Technology in Power Plants

In recent years, the digital twin technology has been gaining popularity in different industries due to the benefits it offers [25–31]. With this technology, operators can monitor the performance of physical systems, identify, and diagnose faults, and improve the efficiencies of these systems. As a result, digital twins have been applied to various power plants to enhance their efficiency. There are several types of power plants, including renewable power plants, such as solar thermal, solar photovoltaic, fuel cells, and wind turbine power plants, and conventional power plants, such as coal-fired, nuclear, diesel-fired, and hydroelectric power plants. Figure 2 depicts the rapid advancement of digital twin technology over the past decade based on the substantial increase in published articles focusing on the application of digital twins in conventional power plants (using the Scopus database). Furthermore, the most prominent applications of digital twins in power plants are hydropower plants, nuclear power plants, and thermal power plants.

The use of digital twin technology in power plants has optimized the performance of various plants, cut down on unplanned downtime, and increased operational efficiency [32,33]. The digital twin can also provide real-time monitoring and control of the plants [30]. In order to do this, the digital twin requires the utilization of sensors and actuators in order to collect data on a wide range of variables, including temperature, pressure, and flow rates. After that, the data is examined, and the analysis results are utilized to optimize the plant's operations in real-time. For instance, if the temperature inside a boiler rises too quickly, the digital twin system may change the air flow fuel, or air flow to keep the boiler from overheating. Furthermore, the digital twin updates plant operators on all the plant operations in real time. This, in return, enables them to recognize failures before they become significant problems. Furthermore, the digital twin can detect failures by applying machine learning algorithms to examine sensor data. In this way, the digital twin technology can detect trends that suggest the possibility of failure in any of the machinery [34–36]. This can aid in reducing equipment downtime and extending the equipment's lifespan. In addition to these advantages, the digital twin can also perform predictive maintenance [37,38]. In predictive maintenance, sensor data and other operational parameters are used to forecast potential faults in equipment before their occurrence. This helps to reduce downtime and extend the equipment's lifetime. As the digital twin offers various services, it optimizes the plant's performance continuously. Consequently, the digital twin can optimize a plant's performance by conducting various simulations and determining the optimal operational parameters [39,40].



	2019	2020	2021	2022	2023
Other Power Plants	18	25	63	80	21
Thermal Power Plants	1	1	5	12	3
Nuclear Power Plants	3	9	14	25	5
Hydropower Plants	2	1	9	5	2

Figure 2. Number of publications related to the applications of digital twins in power plants.

2.1. Thermal Power Plants

The application of digital twin technology in thermal power plants has significantly transformed their operational processes. The creation of a digital model of the power plant's constituents and mechanisms enables operators to gain insights about the plant's functions. Furthermore, it enables the operators to take preventative steps to tackle unexpected problems [41]. Moreover, digital twins allow predictive maintenance strategies and provide the opportunity for simulated testing and enhancement of operations [42]. As a result, incorporating digital twins to thermal power plants enhances efficiency, reliability, and sustainability. Figure 3 depicts the number of publications discussing the integration of digital twins and thermal power plants. The Figure 3 indicates that most researchers use digital twins to control and monitor thermal power plants. On the other hand, other digital twin applications, such optimization, fault detection, and predictive maintenance, have received less attention.

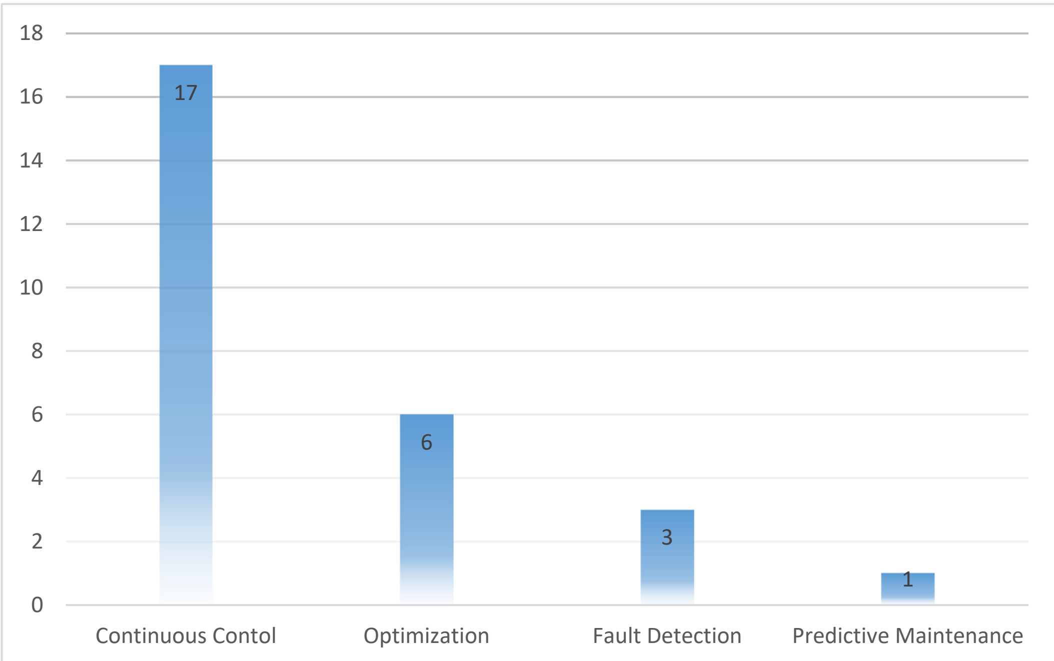


Figure 3. The number of publications in digital twin services for thermal power plants.

In recent years, significant research has been conducted on the optimization of thermal power plants. These investigations aim to improve thermal power plant operations' operational efficiency, profitability, and reliability by employing diverse methodologies and technologies. Henceforth, digital twins have been employed to enhance the thermal efficiency and operational performance of thermal power plants [43]. This was demonstrated in a study conducted by Sleiti et al. [22], where the authors implement the digital twin technology in forthcoming power plants. The authors underscore the significance of heightened dependability, availability, and serviceability in power generation facilities, and advocate for a thorough and robust digital twin framework. Moreover, the study highlights the benefits of utilizing anomaly detection and deep learning algorithms to enhance energy efficiency and transform the energy production industry. Meanwhile, Yu et al. [44] developed a hybrid modeling framework to enhance the performance of functional thermal power plants. The proposed framework integrates physical mechanisms and operational data to develop grey-box models for thermal systems. The authors employed a theoretical framework to analyze an ultra-supercritical double reheat power plant in order to effectively simulate its constituent parts. Additionally, this study highlights the significance of performance monitoring and equipment maintenance, specifically for the steam turbine. Whereas, Spinti et al. [45] focused on enhancing the performance of a biomass-fired tower boiler. The authors emphasized the potential advantages of their methodology, which encompass enhanced boiler efficiency, decreased maintenance costs, and optimized utilization of biomass. Whereas other researchers have explored the improvement of turbomachinery's aerodynamic efficacies. For example, Li et al. [46] proposed using graph learning algorithms to address the deleterious effects of multi-source uncertainty on the efficacy and dependability of energy systems.

The previously mentioned investigations employ digital twin technology, hybrid modeling methodologies, and advanced algorithms to improve thermal power plants' efficiency, reliability, and sustainability. Expanding upon the significance of effective plant operations, Mukherjee et al. [47] presented a two-stage methodology for immediately determining the coal type in thermal power plants. In this study, the authors aim to mitigate the issue of inconsistent coal quality by using sensor data for expeditious coal categorization. The results highlight the significance of coal quality in enhancing the functions of thermal power plants and the possible advantages of monitoring coal quality in real time. As a result, the following benefits are expected: better performance of mills and boilers, decreased emissions, reduced operational expenses, and increased power plant availability. In addition to the enhanced efficiency of the power plant, digital twins can improve resource efficiency. This was illustrated in a study conducted by Ji et al. [24] to highlight the significance of digital twin technology in managing water resources within thermal power plants. The authors employ advanced information technologies and incorporate digital twins to create a sophisticated intelligent water resource management system. This system enables automatic updates, dynamic water balance experimentation, trend prediction, and real-time water modification and enhancement guidance. This research highlights the promising use of digital twin technology in water resource management across various industries, illustrating substantial reductions in water consumption, waste emissions, and associated expenses when it is applied.

Two studies [48,49] have presented distinct methodologies for reconstructing temperature and concentration fields. In one specific investigation [48], researchers focus their research on the concept of sparse reconstruction within the context of an industrial natural gas boiler. The research findings indicate that the utilization of reduced order models (ROMs) in conjunction with sparse reconstruction and nonlinear projection techniques can lead to improved accuracy. Similarly, in a study conducted by Lee et al. [49]; the authors employ proper orthogonal decomposition (POD), Kriging, and a radial basis neural network (RBFN) to construct ROMs for a pulverized coal boiler. The replicated ROMs precisely capture spatial distributions, enabling timely feedback for efficient management and upkeep of combustion facilities.

Detecting faults is critical in ensuring thermal power plants' effective and safe functioning. Researchers have developed the digital twin technology in recent years as a means to create advanced fault detection systems for different power plant components. Digital twin models have improved the precision and efficiency of fault detection systems in various applications such as gas turbines, steam power plants, industrial gas turbines, and turbine blades. For instance, Hu et al. [50] created a digital twin model to suggest a gas-path fault early warning system for gas turbines. Through the integration of a mechanism model with measurement data and the incorporation of an error module, the model's accuracy was enhanced, leading to a reduction in the required modeling time and iterations. This research efficiently detected operational deficiencies in gas turbines while also minimizing the occurrence of false alarms. Similarly, Cruz-Manzo et al. [51] utilized a digital-twin and analytical redundancy strategy to develop a system for diagnosing sensor failures in an industrial gas turbine. The system exhibited the ability to identify, isolate, and withstand sensor anomalies, thereby guaranteeing consistent and reliable operation of the turbine, even in the event of sensor failures. In a similar context, a new methodology has been proposed for anticipating and mitigating low-induced defects in turbine blades by Zhang et al. [52]. The solidification phenomenon was replicated by researchers using a physically grounded numerical model. The manifestation of flaws was investigated by analyzing the impact of internal blade configurations. Furthermore, the application of digital twin technology in overseeing the well-being of machinery was emphasized, particularly in the realms of equipment monitoring and fault detection [53]. This research emphasized the necessity of a more extensive digital twin framework that incorporates all operational scenarios and instances of malfunction, in addition to advanced transfer learning algorithms.

In general, these studies showcase the importance of utilizing the digital twin technology, hybrid modeling frameworks, Bayesian machine learning, and graph learning algorithms to enhance the operational efficiency of thermal power plants. Through the utilization of these technologies, the thermal power plant's efficiency can be enhanced, operational expenses can be curbed, and unforeseeable fluctuations in heat and energy expenses can be adjusted. As a result, the sustainability and dependability of energy generation can be significantly improved. These improvements to the performance of thermal power plants are highly dependent on the implementation of control and monitoring measures. Different investigations focus on different aspects of control and monitoring, covering waste heat recovery, coal quality monitoring, water resource management, and reconstruction of temperature distributions.

2.2. Nuclear Power Plants

Nuclear power plants are advanced facilities that harness energy from nuclear reactions to generate electrical power. Nuclear power plants play a significant role in meeting the growing demand for sustainable and reliable energy resources. Nuclear fission produces a significant quantity of electricity without releasing greenhouse gas emissions [54]. Nuclear power plants offer a reliable and uninterrupted supply of electricity, contributing to global energy's sustainability [54]. Due to their effective functioning and strict compliance with safety regulations, it has become an essential component of the energy mix in many nations across the globe [55]. As a result, many researchers attempted to explore ways to improve nuclear power plants by integrating digital technologies, such as the digital twin technology. Figure 4 illustrates the number of publications related to the applications of digital twins in nuclear power plants based on different services provided by the digital twin. The figure shows an absence of attention to fault identification, as only three publications have focused on this crucial aspect. Additional investigation is required to establish solid and automated algorithms for rapid detection and diagnosis of faults, thereby augmenting the safety of the plant. Furthermore, there is a need for further investigation in the domain of performance prediction, as only three publications have been dedicated to this field.

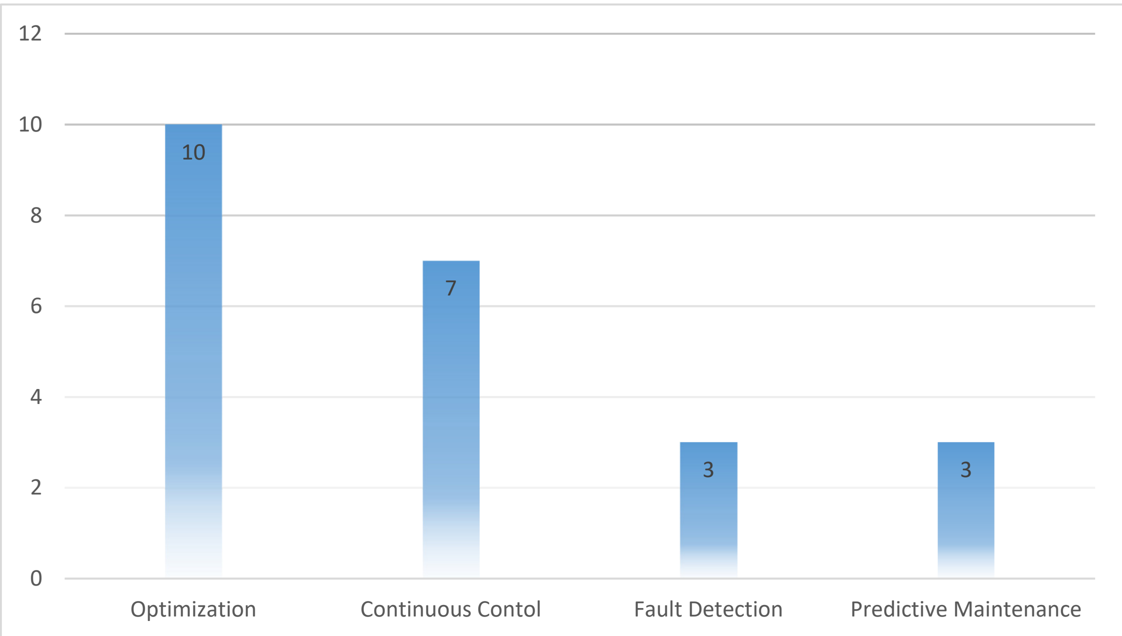


Figure 4. The number of publications in digital twin services for nuclear power plants.

The optimization of nuclear power plant performance is a crucial aspect in ensuring their efficient and reliable operation. Recent research has proposed several methodologies to address various optimization aspects in nuclear power plants. For instance, effective control of the steam pipe network is vital for optimizing the efficiency of nuclear power facilities. In this regard, Sun et al. [23] explored the flow properties of the pipe network using matrix solutions and techniques for identifying anomalies. However, addressing anomalies in highly dynamic situations posed challenges for the outlier resolution method. In order to tackle this problem, a corrective action was implemented, involving offline data correction at a designated pressure point. Furthermore, achieving precise real-time functionality is critically important for optimizing the operation of nuclear power plants. In order to tackle this issue, Song et al. [56] introduced an autonomous calibration method for digital twins of nuclear power plants. This research methodology involved two distinct phases, one offline and one online. The study demonstrated the effectiveness of using clustering and error compensation techniques based on neural networks to improve the calibration accuracy. These studies make valuable contributions towards enhancing the operational efficiency of nuclear power plants. Sun et al. [23] established the foundation for implementing the digital twin framework by utilizing the Improved Particle Swarm Optimization Method (IPSO) method for addressing the steam pipe network. By integrating these methodologies, nuclear power plants can attain efficient flow optimization and real-time calibration, ultimately resulting in improved performance.

In nuclear power plants, digital twins play a crucial role by enabling the monitoring and oversight of plant operations by providing real-time insights into plant behaviour and operational variables. They support proactive maintenance efforts, which, in turn, reduce downtime and enhance asset management. Digital twins also make scenario analysis possible and assist in decision-making, allowing operators to respond effectively to emergencies and optimize the plant's performance. Furthermore, to ensure the safe and efficient operation of nuclear power plants, it is imperative to have real-time monitoring and control. In this context, Gong et al. [57] conducted a study to enhance the Reactor Operation Digital Twin (RODT) for real-time reactor core monitoring. Based on the data obtained while real-time monitoring the physical system, the digital twin is able to make accurate estimations of various parameters. This is demonstrated by Gong et al. [58], where an innovative approach was introduced to utilize a digital twin to estimate input parameters and predict power field outcomes by analysing observed data. The research findings demonstrated the precision and effectiveness of this proposed digital twin in power field forecasting, even in the presence of measurement inaccuracies. This underscores the use of digital twins for remote monitoring within the field of nuclear power plants. In the same way, Yang et al. [59] introduced a novel approach that integrates singular value decomposition (SVD) and deep learning techniques to expedite the estimation process while reducing computational and training costs. The research showcased effective forecasting of intricate fluid dynamics and suggested improvements in neural network models and the integration of advanced fluid mechanics data.

Identifying failures in nuclear power plants is essential to sustain safe and reliable functioning. Faults can result in reduced operational efficiency, equipment malfunctions, and the emergence of safety hazards. Consequently, implementing efficient fault detection methodologies is imperative to reduce downtime, enhance maintenance operations, and enhance the performance of the overall facility. In order to automate the identification and diagnosis of thermal-hydraulic faults in nuclear power plants using digital twins, Nguyen et al. [60] presented a physics-based technique. The study employed principles of physics and simulated sensors to improve the ability to detect faults and offer solutions based on a solid physical understanding. Using real-time data from the plant, the method was shown to be effective in identifying and isolating sensor-related faults in a high-pressure feedwater system.

2.3. Hydropower Plants

Hydropower plants utilize the kinetic energy of water in motion to produce electrical power through a sustainable and environmentally friendly process. Renewable energy sources are essential components of this energy system, as they aid in reducing greenhouse gas emissions and climate change impacts [15]. Hydropower plants present a sustainable and eco-friendly option for fulfilling the increasing global energy demands, owing to their extended lifespan and minimal operational expenses. Hydropower plants offer a reliable and efficient means of generating electricity by harnessing the potential energy of water [61]. This source of energy serves as a reliable power supply for both communities and industries. Due to the importance of hydropower plants, digital twin technology was used for enhancing their performance. Figure 5 displays the number of publications associated with the integration of hydropower plants and digital twins based on the service provided by the digital twin. As shown in Figure 5, limited research investigations have highlighted the significance of optimization, monitoring, and prediction in hydroelectric power generation systems. However, some researchers suggest using digital twins, sensor data, and advanced modeling techniques to enhance maintenance, diagnose faults, predict remaining lifespan, attain autonomous operation, and optimize the performance and durability of power generation infrastructures.

There are a few applications of using digital twins in hydropower plants to optimize, control, monitor, identify faults, and maintain the power plant. However, a recent study was conducted by Wang [62] to forecast the future state of hydraulic electromechanical equipment. The insufficiency of traditional maintenance techniques encouraged the idea of a prognostic maintenance framework that utilizes the digital twin technology. The methodology entailed deploying sensors to gather physical and spatial data. Subsequently, the data was utilized to create a digital twin for qualitative and quantitative assessment. Utilizing an Artificial Neural Network (ANN) algorithm facilitated the fault diagnosis process, while the implementation of transfer learning techniques allowed for a thorough fault diagnosis and accurate prediction of the power plant's lifespan. In the same way, Voronin et al. [63] proposed an effective way to achieve a self-sustaining power plant by reevaluating the infrastructure and integrating reliable energy conversion components. The proposal involves utilizing a digital twin model and integrating diagnostic equipment with a central command to enable continuous monitoring. This, in return, ensures autonomous power generation without human intervention. In addition to these studies, Dreyer et al. [64] proposed a Hydro-Clone system to monitor penstock fatigue by utilizing a digital twin that measures fluctuating pressures. The system efficiently transformed the pressure into stress by utilizing analytical formulas or finite element modeling. The utilization of comparative analysis has revealed the benefits of real-time monitoring and has also highlighted the influence of ancillary services on penstock fatigue. The utilization of Hydro-Clone data has the potential to enhance the performance of turbine governors, reduce fatigue, facilitate inspections, and pinpoint maneuvers that contribute to fatigue, thereby reducing wear.

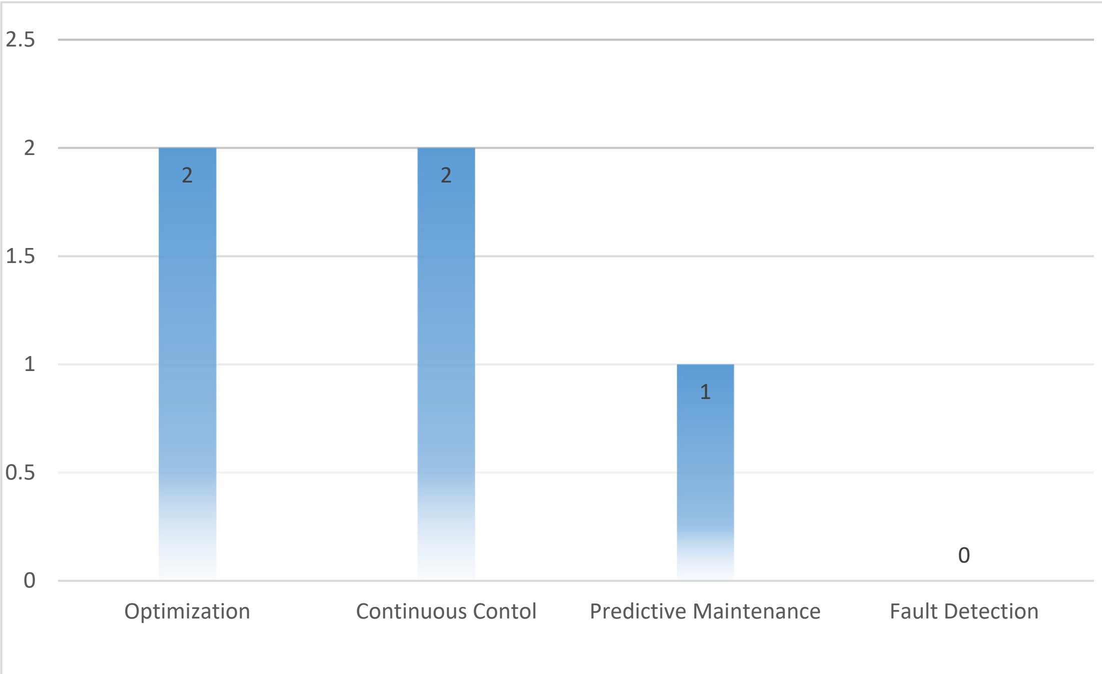


Figure 5. The number of publications in digital twin services for hydropower plants.

3. Digital Twin in Power Plants Analysis

Based on the above sections, digital twins can be used to improve large-scale power plants, such as thermal, nuclear, and hydropower plants. The results of the extensive review of the existing literature on the implementation of digital twin technology in thermal, nuclear, and hydropower plants are summarized in Table 1. The table provides a comprehensive inventory of research activities focusing on the utilization of digital twins in power plants of these categories. Digital twins are being used to improve operational efficiency, fault diagnosis, and maintenance strategies for thermal, nuclear, and hydropower plants.

Table 1 summarizes the main outcomes of the literature review by highlighting how digital twins are applied across various types of power plants, detailing the specific services supported and the algorithms or tools employed. This comparative overview aims to illustrate current trends in digital twin adoption and identify prevalent technologies for each power plant category. Thermal plants show the most diversity in applications and tools, indicating greater maturity. Nuclear power plants find application in digital twin for prediction and fault detection, while hydropower plants is more used in design and monitoring.

As shown from Table 1, the successful implementation of digital twins in power systems include modeling platforms, data analytics tools, machine learning algorithms. Below is a summary of key categories:

- Modeling and Simulation Tools such as MATLAB/Simulink, ANSYS, Modelica, and PROcast are commonly used to develop high-fidelity physical models of power systems, simulating thermal dynamics, fluid flow, and energy balances.
- AI and Machine Learning Platforms like TensorFlow, PyTorch, and Scikit-learn facilitate data-driven modeling, including predictive maintenance, anomaly detection, and optimization using historical and real-

time data and Cloud services enable storage, processing, and analysis of massive datasets required for effective digital twin functionality.

- IoT and Edge Computing such as AWS IoT TwinMaker, Azure Digital Twins, and Siemens MindSphere enable real-time data acquisition, device management, and edge-level decision making.

Table 1. A comparative review of digital twin applications in thermal, nuclear, and hydropower plants.

Component	Service	Software/Algorithm	Ref.
Coal-fired power plant	Investigate potential optimization strategies and prediction	Thermoflow™ software	[65]
Thermal Power Plant	Attain high levels of dependability, availability, and maintainability in future power plants	Vector autoregressive model	[22]
Organic Rankine Cycle	Evaluate the thermodynamic performance	ASPEN Plus model	[66]
Thermal Power Plant	Real-time soft sensing of coal type in thermal power plants.	Semi-supervised cascaded clustering algorithm	[47]
Thermal Power Plant	Improve plant safety and efficiency	Grey-box models and Artificial neural networks	[44]
Thermal Power Plant	Water resource management	Adaptive control program, predictive control program, fuzzy control program and neural network control program	[24]
Biomass Power Plant	Optimize the performance of the biomass-fired tower boiler	Bayesian machine learning	[45]
Natural Gas Boiler	Performance evaluation	Gappy interpolation and radial basis function network	[48]
Coal-fired Power Plant	Rapid evaluation of the effects of varying operation parameters during the design phase and enable real-time response	Proper orthogonal decomposition (POD), Kriging, and a Radial Basis Neural Network (RBFN) regression approach.	[49]
Turbomachinery	Optimizing the aerodynamic performance of turbomachinery.	Dual Graph Neural Network	[46]
Gas Turbine	Fault detection	Self-learning based on kernel density estimation	[50]
Maritime steam power system	Fault detection	Modelica language, and modular modeling	[67]
Gas Turbine	failure diagnosis system	Simulink	[51]
Turbine	Fault detection	ProCAST	[52]
Turbine	Monitoring the performance	-	[33]
Turbine	Fault detection	MATLAB	[53]
Nuclear Power Plants	Optimizing pipe network	Particle swarm optimization	[23]
Nuclear Power Plants	Prediction	Machine learning techniques including k-nearest-neighbors (KNN) and decision trees	[58]
Nuclear Power Plants	Prediction	Singular Value Decomposition (SVD) and deep learning techniques	[59]
Nuclear Power Plants	Monitoring	k-nearest neighbors algorithm (KNN)	[57]
Nuclear Power Plants	Autonomous control	Artificial neural networks and support vector machines	[68]
Nuclear Power Plants	Fault detection	Physics-based model	[60]
Nuclear Power Plants	Autonomous calibration	Artificial neural network	[56]
Hydropower Plants	Prognostic maintenance and health management	Artificial neural network	[62]
Hydropower Plants	Structural evaluation and operational optimization	-	[63]
Hydropower Plants	Evaluation and monitoring	Finite Element Method simulations	[64]

These technologies enable real-time monitoring, simulation, and decision-making in large-scale power plants.

Other than the applications and functions of the digital twin developed for large-scale power plants, the digital twin architecture requires deep understanding. The digital twin architecture utilized in power plants is comprised of a network of interconnected components, including but not limited to sensors, data acquisition systems, cloud-based storage, analytics algorithms, and visualization tools. The technology facilitates instantaneous monitoring, analysis, and enhancement of plant operations, thereby providing operators and engineers with a digital power plant simulation [69]. The implementation of digital twin architecture in power generation facilitates operational efficiency and decision-making processes by collecting data from diverse equipment and systems, utilizing sophisticated analytics, and providing visualization capabilities. Wang et al. [70] have categorized the overall structure of the digital twin into five different layers, namely the physical layer, data layer, mechanism layer, presentation layer, and interaction layer. Figure 6 shows the basic structure of the digital twin in energy systems.

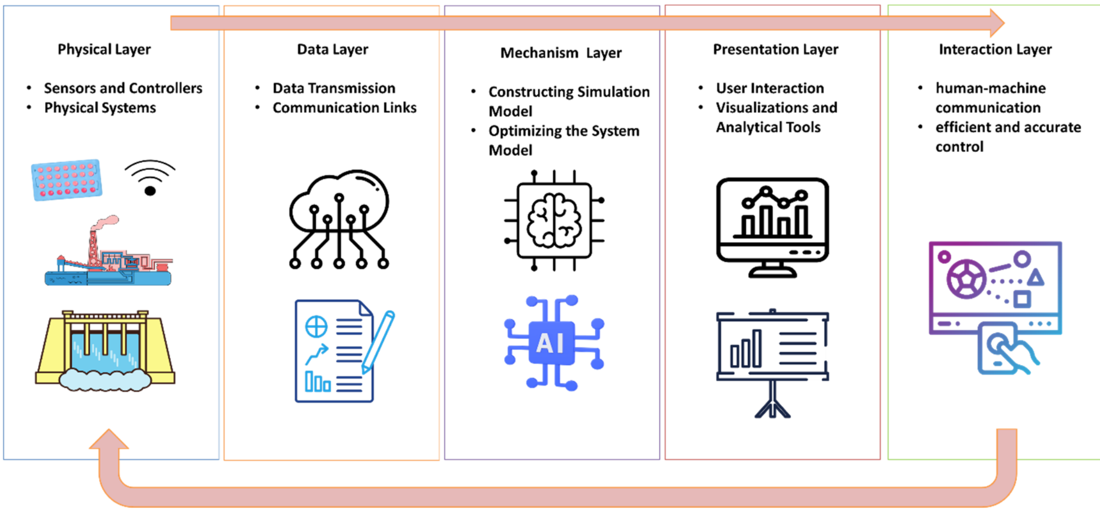


Figure 6. The basic structure of digital twin technology [70].

In the physical layer, equipment has sensors installed in order to conduct regular condition monitoring, and data is gathered through acquisition software. Nevertheless, the coordination among decentralized data collection systems remains an ongoing hurdle. The foundational level of the energy Internet of Things (IoT) platform incorporates extensive data, encompassing physical perception data, model generation data, and virtual reality fusion data. This information originates from smart devices employing advanced sensor technologies, leading to the collection of diverse and varied data types. Furthermore, it fosters the interaction among energy system subsystems with differing protocols, platforms, and interfaces, enabling seamless integration and communication among them. The physical layer of a digital twin for power plants encompasses the elements within a power plant, encompassing items like boilers, turbines, generators, pumps, and valves. Thermal power plants usually consist of a tangible layer composed of diverse elements like boilers, steam turbines, generators, cooling towers, and condensers. In nuclear power plants, the physical layer includes components such as nuclear reactors, control rods, steam generators, and cooling systems. In hydroelectric power generation, tangible infrastructure involves components like dams, penstocks, turbines, and generators. This layer includes information about the plant's design, equipment technical specifications, and operational parameters. Furthermore, this layer incorporates various sensors and monitoring devices that collect real-time data regarding the plant's operational efficiency. This data is then employed to update the other layers of the digital twin.

The data layer utilizes high-speed and low-latency communication links for efficient data transmission. It also performs real-time data cleaning and standardization at the local level of each intelligent device. Furthermore, leveraging data centers and cloud computing allows the system to adapt effectively to changing processing, storage, and operation needs. Digital twins incorporate comprehensive data across the entire lifespan of an intelligent device, whereas traditional condition monitoring relies solely on sensor data. Within a digital twin, the data layer comprises information collected from sensors and monitoring devices positioned in the physical layer. This dataset encompasses various operational parameters like temperature, pressure, and flow rates. The data layer also includes historical data, which can be used to create predictive models for the plant's efficiency. This information is stored in a designated repository and can be accessed and analyzed by other layers of the digital twin.

The simulation model for the smart energy system, constructed based on the digital twin, utilizes a hybrid modeling approach that combines both "model-driven" and "data-driven" techniques. This method adopts system engineering modeling principles and centers around a data chain as its core component. Additionally, it integrates artificial intelligence to continuously update and optimize the system model, resulting in an accurate virtual representation. This model provides essential guidelines for selecting, designing, and producing intelligent devices, going beyond mere decisions based on data changes, such as maintenance or replacement. The mechanism layer within a digital twin aims to capture the fundamental principles of physics and engineering governing the behavior of the plant. This layer consists of mathematical models and algorithms that simulate the behavior of the physical components within the plant. For instance, these models encompass theoretical frameworks for heat transfer, fluid flow dynamics, and the interrelation between heat and other energy forms. These models are used to predict how the plant will respond to varying operational conditions. In thermal power plants, the mechanism layer includes models related to combustion, heat transfer, and fluid flow. In nuclear power plants, it comprises various models concerning neutron behavior, heat transfer, and fluid flow. Hydroelectric power plants typically feature a mechanism layer containing models for water flow, turbine performance, and generator behavior.

The component responsible for user interaction with the digital twin is known as the presentation layer. This layer includes various visualizations and analytical tools designed to facilitate the monitoring of the plant's operational efficiency, enabling operators and engineers to make informed decisions. For instance, it may incorporate dashboards displaying real-time data, trend charts highlighting changes over time, and alert systems notifying operators of potential issues. The presentation layer for thermal, nuclear, and hydro power plants can include different visualizations and tools tailored to the specific needs of each plant. Common instruments used in this context include real-time monitoring interfaces, graphical representations of trends over time, and alert systems. The presentation layer is interconnected to the interaction layer. The interaction layer goes beyond traditional flat or simple three-dimensional displays. It enables real-time immersive interaction between users and the models. This interactive experience is made possible by establishing communication channels between individuals and intelligent devices, using technologies like speech recognition, posture analysis, and visual tracking. This realistic connection allows for effective and precise control of various grids, such as the power grid, gas grid, heat grid, transportation grid, and water grid, through multiple channels, facilitating interactive management.

While digital twin (DT) applications have traditionally focused on thermal, nuclear, and hydropower plants, recent advancements have extended their utility to emerging power system technologies. These include Power-to-X (PtX) systems, renewable-integrated heating networks, hybrid grids, and energy storage systems—all of which require real-time coordination, optimization, and forecasting. Overall, digital twins are proving essential for facilitating the flexible, efficient, and resilient operation of advanced and integrated power systems [44–66].

4. Conclusions and Research Challenges

The incorporation of contemporary machine learning and artificial intelligence capabilities has led to the emergence of digital twin technology. The technology facilitates the integration of information between virtual and physical models, enabling the exchange of information between digital and physical representations of energy systems. Initially, it generates forecasts through the utilization of extensive data, a well-defined approach, and exhaustive information. This technology offers considerable advantages to businesses, such as expediting risk assessment and production timelines, enabling predictive maintenance, facilitating real-time remote monitoring, and enhancing financial decision-making. Due to these advantages, the digital twin technology has been developed for numerous applications. One of these applications is power plants, including thermal, hydro, and nuclear power plants. The implementation of a digital twin for power plants has the potential to offer significant benefits to both industrial and large-scale projects. These benefits include the ability to predict power output and efficiency, optimize equipment-related parameters, and detect various types of system faults. There seems to be a significant gap in the current literature regarding fault detection and predictive maintenance for large-scale power plants that employ digital twins. The field of study in question exhibits significant promise in enhancing power facilities' efficiency, dependability, and economic viability via sophisticated computational simulations and anticipatory statistical analysis. Nonetheless, the restricted focus on this intersection impedes advancement and originality in the discipline. By allocating greater attention, resources, and cooperative endeavors to this subject matter, researchers will understand the complex concepts of fault detection and anticipated maintenance in relation to digital twins of power plants. This investigation has the potential to provide valuable perspectives and approaches that can substantially improve the effectiveness, security, and environmental friendliness of electricity production. By dedicating more resources and conducting focused research, it is possible to facilitate significant progress in the power industry, thereby guaranteeing the dependable and robust functioning of extensive power facilities.

The technology of digital twins is emerging as a promising innovation in the domain of large-scale power plants. The digital twin technology provides a virtual copy of the physical power plant to provide valuable insights, optimize operations, and improve the plant's overall performance. Nevertheless, the implementation of digital twins in intricate and vast settings presents an individual set of barriers and challenges. For example, data integration and quality present a considerable challenge, given that large-scale power plants generate numerous and diverse information from multiple origins. The process of consolidating and coordinating diverse data sets, which may exhibit variations in structure and resolution, is imperative to uphold the authenticity and dependability of the digital twin [71,72]. Another significant challenge revolves around scalability, stemming from the necessity to faithfully depict the interactions and interdependencies among interconnected components throughout the entire power plant. Overcoming this challenge involves expanding the digital twin model's scale while maintaining high performance and computational efficiency [73–75]. As a result, attaining model complexity and precision is challenging, given the involvement of various disciplines and systems in power plant operations that necessitate precise representation in the digital twin. The maintenance of high-fidelity modeling is of utmost importance in order to avert the possibility of unreliable predictions and suboptimal decision-making. Furthermore, the acquisition and processing of real-time data from multiple sensors and devices gives rise to concerns regarding latency and synchronization between the digital twin and the physical plant [76].

Securing digital twins is paramount, especially considering that power plants are deemed critical infrastructure and susceptible to cyber threats. Safeguarding the operations of a power plant requires the adoption of robust cybersecurity measures to preserve data integrity and prevent unauthorized access to the digital twin. Integrating diverse systems and components from different providers into the digital twin presents challenges related to interoperability and standardization. The absence of uniform protocols and data formats among these providers complicates the integration process, highlighting the importance of standardized protocols and common standards [77]. Additionally, effectively harnessing the vast data and insights generated by digital twins for decision-making processes requires training operators and staff to comprehend and apply the provided information. Striking the right equilibrium between automation and human expertise and judgment is crucial for maintaining the safety and efficiency of power plant operations [78]. Overcoming these challenges is pivotal for successfully integrating and utilizing digital twins in large-scale power plants.

Another critical challenge in implementing digital twins in power plants is the interoperability i.e., the need for interconnection and communication among various system components. A digital twin must integrate real-time data from a wide range of components. These components often operate across different communication protocols and platforms, creating potential incompatibilities. Effective communication infrastructure is, therefore essential for operating a digital twin.

The key findings of this work are summarised as follows:

1. Digital twin technology is most mature in thermal power plant applications, with diverse tools and advanced use in optimization and fault detection.
2. Nuclear power applications focus on predictive analytics and automation.
3. Hydropower integration remains underexplored; recent studies show potential in lifespan prediction and structural health monitoring.

These insights emphasize the transformative potential of digital twins in power systems. Future research should focus on developing standardized frameworks, addressing data integration issues, and exploring applications of DTs. Future studies should focus on establishing unified and standardized frameworks that outline specific protocols, structured data models, and communication guidelines to facilitate smooth interoperability among various digital twin systems and components. A significant focus should be placed on resolving data integration difficulties, which involve aligning diverse data formats, acquiring real-time data, synchronizing inputs from multiple sources, and handling extensive, high-speed data flows. In addition, upcoming research should explore sophisticated algorithms for merging data, conducting predictive analysis, and applying machine learning techniques to improve digital twin technologies' precision, flexibility, and intelligence.

Author Contributions

C.S.: Conceptualization; methodology; validation; formal analysis; investigation; data curation; writing—original draft preparation; writing—review and editing; H.A.: Conceptualization; validation; data curation; writing—original draft preparation. A.H.I.M.: Conceptualization; validation; data curation; writing—original draft preparation. M.A.A.: visualization; supervision; validation. A.G.O.: visualization; supervision; validation. All authors have read and agreed to the published version of the manuscript.

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The authors declare no conflict of interest. Given the role as Editor-in-Chief, A.G.O. had no involvement in the peer review of this paper and had no access to information regarding its peer-review process. Full responsibility for the editorial process of this paper was delegated to another editor of the journal.

Use of AI and AI-assisted Technologies

No AI tools were utilized for this paper.

Abbreviations

Abbreviation	Description
DT	Digital Twin
ANN	Artificial Neural Network
ROM	Reduced Order Model
IoT	Internet of Things
SVD	Singular Value Decomposition
RBFN	Radial Basis Function Network
POD	Proper Orthogonal Decomposition
KNN	K-Nearest Neighbors
PtX	Power-to-X
IPSO	Improved Particle Swarm Optimization
OPC-UA	Open Platform Communications Unified Architecture
CSP	Concentrating Solar Power
LSTM	Long Short-Term Memory (Neural Network)

References

1. Dassisti, M.; Giovannini, A.; Merla, P.; et al. An Approach to Support Industry 4.0 Adoption in SMEs Using a Core-Metamodel. *Annu. Rev. Control* **2019**, *47*, 266–274. https://doi.org/10.1016/J.ARCONTROL.2018.11.001.
2. Grieves, M.; Vickers, J. Grieves Origins of the Digital Twin Concept. *Fla. Inst. Technol.* **2016**, *8*, 3–20. https://doi.org/10.13140/RG.2.2.26367.61609.
3. Glaessgen, E.; Stargel, D. The digital twin paradigm for future NASA and US Air Force vehicles. In Proceedings of the 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference 20th AIAA/ASME/AHS Adaptive Structures Conference 14th AIAA, Honolulu, HI, USA, 23–26 April 2012; p. 1818.
4. Chen, Y. Integrated and Intelligent Manufacturing: Perspectives and Enablers. *Engineering* **2017**, *3*, 588–595.
5. Liu, Z.; Meyendorf, N.; Mrad, N. The role of data fusion in predictive maintenance using digital twin. In *AIP Conference Proceedings*; AIP Publishing LLC: Melville, NY, USA, 2018; p. 20023.
6. Semeraro, C.; Lezoche, M.; Panetto, H.; et al. Digital Twin Paradigm: A Systematic Literature Review. *Comput. Ind.* **2021**, *130*, 103469.
7. Alobaid, F.; Mertens, N.; Starkloff, R.; et al. Progress in Dynamic Simulation of Thermal Power Plants. *Prog. Energy Combust. Sci.* **2017**, *59*, 79–162. https://doi.org/10.1016/j.pecs.2016.11.001.
8. Masuyama, F. History of Power Plants and Progress in Heat Resistant Steels. *ISIJ Int.* **2001**, *41*, 612–625.
9. Adibhatla, S.; Kaushik, S.C. Energy and Exergy Analysis of a Super Critical Thermal Power Plant at Various Load Conditions under Constant and Pure Sliding Pressure Operation. *Appl. Therm. Eng.* **2014**, *73*, 51–65. https://doi.org/10.1016/j.applthermaleng.2014.07.030.
10. Alami, A.H.; Olabi, A.G.; Mdallal, A.; et al. Concentrating Solar Power (CSP) Technologies: Status and Analysis. *Int. J. Thermofluids* **2023**, *18*, 100340. https://doi.org/10.1016/J.IJFT.2023.100340.
11. Tritt, T.M.; Böttner, H.; Chen, L. Thermoelectrics: Direct Solar Thermal Energy Conversion. *MRS Bull.* **2008**, *33*, 366–368. https://doi.org/10.1557/MRS2008.73.
12. Olesen, J.F.; Shaker, H.R. Predictive Maintenance for Pump Systems and Thermal Power Plants: State-of-the-Art Review, Trends and Challenges. *Sensors* **2020**, *20*, 2425. https://doi.org/10.3390/S20082425.
13. Kuria, M. Operational Challenges Facing Performance of Thermal Power Plants in Kenya. 2013. Available online: http://erepository.uonbi.ac.ke/handle/11295/58576 (accessed on 9 April 2023).

14. Porton, M.; Latham, H.; Vizvary, Z.; et al. Balance of plant challenges for a near-term EU demonstration power plant. In Proceedings of the 2013 IEEE 25th Symposium on Fusion Engineering, SOFE, San Francisco, CA, USA, 10–14 June 2013. https://doi.org/10.1109/SOFE.2013.6635331.
15. Sayed, E.T.; Olabi, A.G.; Alami, A.H.; et al. Renewable Energy and Energy Storage Systems. *Energies* **2023**, *16*, 1415. https://doi.org/10.3390/EN16031415.
16. Mahmoud, M.; Dutton, K.; Denman, M. Dynamical Modelling and Simulation of a Cascaded Reserevoirs Hydropower Plant. *Electr. Power Syst. Res.* **2004**, *70*, 129–139. https://doi.org/10.1016/J.EPSR.2003.12.001.
17. Cuartas, L.A.; Cunha, A.P.M.D.A.; Alves, J.A.; et al. Recent Hydrological Droughts in Brazil and Their Impact on Hydropower Generation. *Water* **2022**, *14*, 601. https://doi.org/10.3390/W14040601/S1.
18. Losier, L.-M.; Fernandes, R.; Tabarro, P.; et al. The Importance of Digital Twins for Resilient Infrastructure A Bentley White Paper. 201. Available online: www.bentley.com (accessed on 25 April 2023).
19. Ghenai, C.; Husein, L.A.; Al Nahlawi, M.; et al. Recent Trends of Digital Twin Technologies in the Energy Sector: A Comprehensive Review. *Sustain. Energy Technol. Assess.* **2022**, *54*, 102837. https://doi.org/10.1016/J.SETA.2022.102837.
20. Semeraro, C.; Aljaghoub, H.; Abdelkareem, M.A.; et al. Digital Twin in Battery Energy Storage Systems: Trends and Gaps Detection through Association Rule Mining. *Energy* **2023**, *273*, 127086. https://doi.org/10.1016/J.ENERGY.2023.127086.
21. Semeraro, C.; Olabi, A.G.; Aljaghoub, H.; et al. Digital Twin Application in Energy Storage: Trends and Challenges. *J. Energy Storage* **2023**, *58*, 106347. https://doi.org/10.1016/J.EST.2022.106347.
22. Sleiti, A.K.; Kapat, J.S.; Vesely, L. Digital Twin in Energy Industry: Proposed Robust Digital Twin for Power Plant Andother Complex Capital-Intensive Large Engineering Systems. *Energy Rep.* **2022**, *8*, 3704–3726. https://doi.org/10.1016/J.EGYR.2022.02.305.
23. Sun, J.; Zhang, B.; Cheng, S.; et al. Investigation of Single Pressure Point Off-Line Correction in Matrix-Solved Steam Pipe Network Model for Digital Twins Application. *Ann. Nucl. Energy* **2022**, *179*, 109426. https://doi.org/10.1016/J.ANUCENE.2022.109426.
24. Ji, H.; Li, J.; Zhang, S.; et al. Research on Water Resources Intelligent Management of Thermal Power Plant Based on Digital Twins. In Proceedings of the 2021 IEEE 6th International Conference on Cloud Computing and Big Data Analytics, ICCCBDA, Chengdu, China, 24–26 April 2021; pp. 557–562. https://doi.org/10.1109/ICCCBDA51879.2021.9442503.
25. Tao, F.; Zhang, H.; Liu, A.; et al. Nee Digital Twin in Industry: State-of-the-Art. *IEEE Trans. Ind. Inform.* **2018**, *15*, 2405–2415.
26. Liu, M.; Fang, S.; Dong, H.; et al. Review of Digital Twin about Concepts, Technologies, and Industrial Applications. *J. Manuf. Syst.* **2021**, *58*, 346–361.
27. Schmitt, J.; Horstkötter, I.; Bäker, B. State-of-Health Estimation by Virtual Experiments Using Recurrent Decoder–Encoder Based Lithium-Ion Digital Battery Twins Trained on Unstructured Battery Data. *J. Energy Storage* **2023**, *58*, 106335. https://doi.org/10.1016/j.est.2022.106335.
28. Yi, Y.; Xia, C.; Feng, C.; et al. Digital Twin-Long Short-Term Memory (LSTM) Neural Network Based Real-Time Temperature Prediction and Degradation Model Analysis for Lithium-Ion Battery. *J. Energy Storage* **2023**, *64*, 107203. https://doi.org/10.1016/j.est.2023.107203.
29. Yuan, Z.; Pan, Y.; Wang, H.; et al. Fault Data Generation of Lithium Ion Batteries Based on Digital Twin: A Case for Internal Short Circuit. *J. Energy Storage* **2023**, *64*, 107113. https://doi.org/10.1016/j.est.2023.107113.
30. Li, W.; Rentemeister, M.; Badeda, J.; et al. Digital Twin for Battery Systems: Cloud Battery Management System with Online State-of-Charge and State-of-Health Estimation. *J. Energy Storage* **2020**, *30*, 101557.
31. Tang, H.; Wu, Y.; Cai, Y.; et al. Design of Power Lithium Battery Management System Based on Digital Twin. *J. Energy Storage* **2022**, *47*, 103679. https://doi.org/10.1016/j.est.2021.103679.
32. Moghadam, H.M.; Foroozan, H.; Gheisarnejad, M.; et al. A Survey on New Trends of Digital Twin Technology for Power Systems. *J. Intell. Fuzzy Syst.* **2021**, *41*, 3873–3893. https://doi.org/10.3233/JIFS-201885.
33. Yu, J.; Liu, P.; Li, Z. Hybrid Modelling and Digital Twin Development of a Steam Turbine Control Stage for Online Performance Monitoring. *Renew. Sustain. Energy Rev.* **2020**, *133*, 110077. https://doi.org/10.1016/J.RSER.2020.110077.
34. Pei, F.Q.; Tong, Y.F.; Yuan, M.H.; et al. The Digital Twin of the Quality Monitoring and Control in the Series Solar Cell Production Line. *J. Manuf. Syst.* **2021**, *59*, 127–137. https://doi.org/10.1016/J.JMSY.2021.02.001.
35. Al-Ali, A.R.; Gupta, R.; Batool, T.Z.; et al. Digital Twin Conceptual Model within the Context of Internet of Things. *Future Internet* **2020**, *12*, 163. https://doi.org/10.3390/FI12100163.
36. Li, M.; Lu, Q.; Bai, S.; et al. Digital Twin-Driven Virtual Sensor Approach for Safe Construction Operations of Trailing Suction Hopper Dredger. *Autom. Constr.* **2021**, *132*, 103961. https://doi.org/10.1016/J.AUTCON.2021.103961.
37. Warke, V.; Kumar, S.; Bongale, A.; et al. Sustainable Development of Smart Manufacturing Driven by the Digital Twin Framework: A Statistical Analysis. *Sustainability* **2021**, *13*, 10139. https://doi.org/10.3390/SU131810139.
38. Werner, A.; Zimmermann, N.; Lentes, J. Approach for a Holistic Predictive Maintenance Strategy by Incorporating a Digital Twin. *Procedia Manuf.* **2019**, *39*, 1743–1751. https://doi.org/10.1016/J.PROMFG.2020.01.265.

39. Falekas, G.; Karlis, A. Digital Twin in Electrical Machine Control and Predictive Maintenance: State-of-the-Art and Future Prospects. *Energies* **2021**, *14*, 5933. https://doi.org/10.3390/EN14185933.
40. Leng, J.; Wang, D.; Shen, W.; et al. Digital Twins-Based Smart Manufacturing System Design in Industry 4.0: A Review. *J. Manuf. Syst.* **2021**, *60*, 119–137. https://doi.org/10.1016/J.JMSY.2021.05.011.
41. Qi, Q.; Tao, F.; Hu, T.; et al. Enabling Technologies and Tools for Digital Twin. *J. Manuf. Syst.* **2021**, *58*, 3–21. https://doi.org/10.1016/J.JMSY.2019.10.001.
42. Semeraro, C.; Lezoche, M.; Panetto, H.; et al. Data-Driven Invariant Modelling Patterns for Digital Twin Design. *J. Ind. Inf. Integr.* **2023**, *31*, 100424. https://doi.org/10.1016/J.JII.2022.100424.
43. Semeraro, C.; Aljaghoub, H.; Abdelkareem, M.A.; et al. Guidelines for Designing a Digital Twin for Li-Ion Battery: A Reference Methodology. *Energy* **2023**, *284*, 128699. https://doi.org/10.1016/J.ENERGY.2023.128699.
44. Yu, J.; Petersen, N.; Liu, P.; et al. Hybrid Modelling and Simulation of Thermal Systems of in-Service Power Plants for Digital Twin Development. *Energy* **2022**, *260*, 125088. https://doi.org/10.1016/J.ENERGY.2022.125088.
45. Spinti, J.P.; Smith, P.J.; Smith, S.T. Atikokan Digital Twin: Machine Learning in a Biomass Energy System. *Appl. Energy* **2022**, *310*, 118436. https://doi.org/10.1016/J.APENERGY.2021.118436.
46. Li, J.; Liu, T.; Zhu, G.; et al. Uncertainty Quantification and Aerodynamic Robust Optimization of Turbomachinery Based on Graph Learning Methods. *Energy* **2023**, *273*, 127289. https://doi.org/10.1016/J.ENERGY.2023.127289.
47. Mukherjee, T.; Gupta, A.; Deodhar, A.; et al. Real-Time Coal Classification in Thermal Power Plants. *Control Eng. Pract.* **2023**, *130*, 105377. https://doi.org/10.1016/J.CONENGPRAC.2022.105377.
48. Park, J.; Lee, W.; Huh, K.Y. Model Order Reduction by Radial Basis Function Network for Sparse Reconstruction of an Industrial Natural Gas Boiler. *Case Stud. Therm. Eng.* **2022**, *37*, 102288. https://doi.org/10.1016/J.CSITE.2022.102288.
49. Lee, W.; Jang, K.; Han, W.; et al. Model Order Reduction by Proper Orthogonal Decomposition for a 500 MWe Tangentially Fired Pulverized Coal Boiler. *Case Stud. Therm. Eng.* **2021**, *28*, 101414. https://doi.org/10.1016/J.CSITE.2021.101414.
50. Hu, M.; He, Y.; Lin, X.; et al. Digital Twin Model of Gas Turbine and Its Application in Warning of Performance Fault. *Chin. J. Aeronaut.* **2023**, *36*, 449–470. https://doi.org/10.1016/J.CJA.2022.07.021.
51. Cruz-Manzo, S.; Panov, V.; Bingham, C. GAS Turbine Sensor Fault Diagnostic System in a Real-Time Executable Digital-Twin. *J. Glob. Power Propuls. Soc.* **2023**, *7*, 85–94. https://doi.org/10.33737/JGPPS/159781.
52. Zhang, H.; Liu, X.; Ma, D.; et al. Digital Twin for Directional Solidification of a Single-Crystal Turbine Blade. *Acta Mater.* **2023**, *244*, 118579. https://doi.org/10.1016/J.ACTAMAT.2022.118579.
53. Wang, J.; Zhang, Z.; Liu, Z.; et al. Digital Twin Aided Adversarial Transfer Learning Method for Domain Adaptation Fault Diagnosis. *Reliab. Eng. Syst. Saf.* **2023**, *234*, 109152. https://doi.org/10.1016/J.RESS.2023.109152.
54. Ağbulut, Ü. Turkey's Electricity Generation Problem and Nuclear Energy Policy. *Energy Sources Part. A: Recovery Util. Environ. Eff.* **2019**, *41*, 2281–2298. https://doi.org/10.1080/15567036.2019.1587107.
55. Adams, S.; Odonkor, S. Status, Opportunities, and Challenges of Nuclear Power Development in Sub-Saharan Africa: The Case of Ghana. *Progress. Nucl. Energy* **2021**, *138*, 103816. https://doi.org/10.1016/J.PNUCENE.2021.103816.
56. Song, H.; Song, M.; Liu, X. Online Autonomous Calibration of Digital Twins Using Machine Learning with Application to Nuclear Power Plants. *Appl. Energy* **2022**, *326*, 119995. https://doi.org/10.1016/J.APENERGY.2022.119995.
57. Gong, H.; Zhu, T.; Chen, Z.; et al. Parameter Identification and State Estimation for Nuclear Reactor Operation Digital Twin. *Ann. Nucl. Energy* **2023**, *180*, 109497. https://doi.org/10.1016/J.ANUCENE.2022.109497.
58. Gong, H.; Cheng, S.; Chen, Z.; et al. An Efficient Digital Twin Based on Machine Learning SVD Autoencoder and Generalised Latent Assimilation for Nuclear Reactor Physics. *Ann. Nucl. Energy* **2022**, *179*, 109431. https://doi.org/10.1016/J.ANUCENE.2022.109431.
59. Yang, J.; Sui, X.; Huang, Y.; et al. Assessment of Reactor Flow Field Prediction Based on Deep Learning and Model Reduction. *Ann. Nucl. Energy* **2022**, *179*, 109367. https://doi.org/10.1016/J.ANUCENE.2022.109367.
60. Nguyen, T.N.; Ponciroli, R.; Bruck, P.; et al. A digital Twin Approach to System-Level Fault Detection and Diagnosis for Improved Equipment Health Monitoring. *Ann. Nucl. Energy* **2022**, *170*, 109002. https://doi.org/10.1016/J.ANUCENE.2022.109002.
61. Alnaqbi, S.; Alasad, S.; Aljaghoub, H.; et al. Applicability of Hydropower Generation and Pumped Hydro Energy Storage in the Middle East and North Africa. *Energies* **2022**, *15*, 2412. https://doi.org/10.3390/en15072412.
62. Wang, Z.; Jia, W.; Wang, K.; et al. Digital twins supported equipment maintenance model in intelligent water conservancy. *Comput. Electr. Eng.* **2022**, *101*, 108033. https://doi.org/10.1016/J.COMPELECENG.2022.108033.
63. Voronin, S.; Davlatov, A.; Kosimov, B. Development directions of power supply for rural areas of Tajikistan. In Proceedings of the 2019 International Ural Conference on Electrical Power Engineering, UralCon 2019, Chelyabinsk, Russia, 1–3 October 2019; pp. 157–161. https://doi.org/10.1109/URALCON.2019.8877688.
64. Dreyer, M.; Nicolet, C.; Gaspoz, A.; et al. Monitoring 4.0 of Penstocks: Digital Twin for Fatigue Assessment. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *774*, 012009. https://doi.org/10.1088/1755-1315/774/1/012009.

65. Xu, B.; Wang, J.; Wang, X.; et al. A Case Study of Digital-Twin-Modelling Analysis on Power-Plant-Performance Optimizations. *Clean. Energy* **2019**, *3*, 227–234. https://doi.org/10.1093/ce/zkz025.
66. Popp, T.; Heberle, F.; Weiß, A.P.; et al. Thermodynamic evaluation of an orc test rig-from comprehensive experimental results to a simulation model. In Proceedings of the 6th International Seminar on ORC Power Systems, Munich, Germany, 11–13 October 2021. Available online: https://www.researchgate.net/profile/Tobias-Popp/publication/357242413_THERMODYNAMIC_EVALUATION_OF_AN_ORC_TEST_RIG_-_FROM_COMPREHENSIVE_EXPERIMENTAL_RESULTS_TO_A_SIMULATION_MODEL/links/61c3040f52bd3c7e0583c739/THERMODYNAMIC-EVALUATION-OF-AN-ORC-TEST-RIG-FROM-COMPREHENSIVE-EXPERIMENTAL-RESULTS-TO-A-SIMULATION-MODEL.pdf (accessed on 20 June 2025).
67. Zeng, G.; Wang, J.; Zhang, L.; et al. Multi-Domain Modeling and Analysis of Marine Steam Power System Based on Digital Twin. *J. Mar. Sci. Eng.* **2023**, *11*, 429. https://doi.org/10.3390/JMSE11020429.
68. Sandhu, H.K.; Bodda, S.S.; Gupta, A. A Future with Machine Learning: Review of Condition Assessment of Structures and Mechanical Systems in Nuclear Facilities. *Energies* **2023**, *16*, 2628. https://doi.org/10.3390/EN16062628.
69. Tang, W.; Chen, X.; Qian, T.; et al. Technologies and Applications of Digital Twin for Developing Smart Energy Systems. *Chin. J. Eng. Sci.* **2020**, *22*, 74. https://doi.org/10.15302/J-SSCAE-2020.04.010.
70. Wang, Y.; Su, Z.; Guo, S.; et al. A Survey on Digital Twins: Architecture, Enabling Technologies, Security and Privacy, and Future Prospects. *IEEE Internet Things J.* **2023**, *10*, 14965–14987. https://doi.org/10.1109/JIOT.2023.3263909.
71. Mozo, A.; Karamchandani, A.; Gómez-Canaval, S.; et al. B5GEMINI: AI-Driven Network Digital Twin. *Sensors* **2022**, *22*, 4106. https://doi.org/10.3390/S22114106.
72. Khan, L.U.; Saad, W.; Niyato, D.; et al. Digital-Twin-Enabled 6G: Vision, Architectural Trends, and Future Directions. *IEEE Commun. Mag.* **2022**, *60*, 74–80. https://doi.org/10.1109/MCOM.001.21143.
73. Aydemir, H.; Zengin, U.; Durak, U.; et al. The Digital Twin Paradigm for Aircraft–Review and Outlook. *AIAA Scitech* **2020**, *1*, 1–12. https://doi.org/10.2514/6.2020-0553.
74. López, C.E.B. Real-Time Event-Based Platform for the Development of Digital Twin Applications. *Int. J. Adv. Manuf. Technol.* **2021**, *116*, 835–845. https://doi.org/10.1007/S00170-021-07490-9/METRICS.
75. Faleiro, R.; Pan, L.; Pokhrel, S.R.; et al. Digital Twin for Cybersecurity: Towards Enhancing Cyber Resilience. *Lect. Notes Inst. Comput. Sci. Soc. Inform. Telecommun. Eng. LNICST* **2022**, *413*, 57–76. https://doi.org/10.1007/978-3-030-93479-8_4/COVER.
76. Eckhart, M.; Ekelhart, A. Digital Twins for Cyber-Physical Systems Security: State of the Art and Outlook. *Secur. Qual. Cyber Phys. Syst. Eng.* **2019**, 383–412. https://doi.org/10.1007/978-3-030-25312-7_14/COVER.
77. Romero, D.; Bernus, P.; Noran, O.; et al. The operator 4.0: Human cyber-physical systems & adaptive automation towards human-automation symbiosis work systems. In *Advances in Production Management Systems. Initiatives for a Sustainable World*; IFIP Advances in Information and Communication Technology; Nääs, I., Vendrametto, O., Reis, J.M., et al., Eds.; Springer International Publishing: Cham, Switzerland, 2016; Volume 488, pp. 677–686. https://doi.org/10.1007/978-3-319-51133-7_80.
78. Gobio-Thomas, L.B.; Darwish, M.; Stojceska, V. Review on the Economic Impacts of Solar Thermal Power Plants. *Therm. Sci. Eng. Prog.* **2023**, *46*, 102224. https://doi.org/10.1016/j.tsep.2023.102224.