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Energy 4.0: Challenges and Enablers of Digital Twin Application in Power Plant

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Abstract: Digital twins have recently garnered attention as digital solutions in "Energy 4.0" that will reshape the future of the power generation industry toward the digitalization era. It is supported by the rapid advancement of data connectivity and computational power that intensifies the potential of the digital twin approach in addressing the energy trilemma. Despite its popularity, the preliminary analysis revealed a lack of publications discussing the implementation of digital twins in the power generation industry. The researcher may find the difficulties and face the issues that prevent them from exploring this study area. Therefore, this article will perform a literature review of the selected publications to analyze the challenges and enablers of the digital twin implementation in power plants. The selection of articles from multiple databases is refined based on keywords search, publication time frame, and inclusion criteria. The study found that the challenges can be divided into nine categories, and eight enablers have been identified to address the issues that arise in digital twin applications. The findings contribute to the body of knowledge on digital twin applications by proposing the operational ecosystem framework to illustrate the interaction between enablers and challenges.

Keywords: Challenges, Digital Twin, Enablers, Machine Learning, Power Plant.

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1. INTRODUCTION

The rapid advancement of technology in the era of the 4IR has led to significant improvements in data connectivity and computational power. The Internet of Things (IoT) technology revolution has influenced the emergence of big data and cloud computing, allowing for advanced monitoring and performance insight. IoT technology benefited plant personnel in the power plant context by increasing data collection and critical parameters unavailable in distributed control systems (DCS). These factors will intensify the potential of the digital twin approach to become a new technology to embrace. Adopting the digital twin approach as digital solutions will allow the cutting-edge platform to manage the power plant asset throughout its life cycle, aiming to be more sustainable, resilient, and efficient.

A digital transformation is vital in the energy sector to reshape the future of electricity. It is driven by the Energy 4.0 revolution in powering the new electric world toward digitalization. This ecosystem utilizes extensive artificial intelligence (AI) and big data to assist decision-making, improve energy efficiency, reduce emissions, and mitigate climate impact. This initiative should be aligned with the energy trilemma to address the main issues in global challenges: energy security, equity, and environmental sustainability. According to a preliminary study, the "digital twin" concept has been accepted across various industries: manufacturing [1 ; 2], aviation [3; 4 ; 5], oil and gas [6], construction [7], safety management [8] and healthcare [9].

However, this study found a lack of rigorous research in a comprehensive review of the prior literature due to the limited number of publications discussing the application of digital twins in power plant contexts. In addition, there is no discussion on the digital twin application framework for the power generation industry. Consequently, the researcher may find difficulties and face certain issues that prevent them from exploring this study area. Therefore, this article will analyze the publication trends from 2016 to 2021 in order examine the challenges and enablers of digital twin applications in power plants. Later, the relationship between these elements will be discussed according to the proposed conceptual framework. The findings of this study can be used as a reference to expand a study in this area.

This study is driven by the two (2) research questions as follows:

RQ1: What are the challenges and enablers of the digital twin implementation in the power generation industry from 2016 to 2021?

RQ2: What are the relationships between the enablers and challenges in implementing digital twins in the power generation industry?

2. DIGITAL TWIN SURVEY

The recent emergence and integration of digital twin technology in the engineering and energy domains has sparked widespread interest, as evidenced by an extensive body of review literature developed over the past five years period of 2016-2021. An optimistic outlook on the impact of this technology is well-founded, considering the substantial research efforts exploring its applications and theoretical foundations. A thorough literature search across the databases SCOPUS and Science Direct yielded 386 review articles, which were systematically analyzed into a core group of 135 papers for detailed analysis. These reviews were systematically organized and presented in **Table 1** to demonstrate collective scholarly diligence. It provides a comprehensive view of current digital twin research, with notable emphasis on the manufacturing and construction sectors.

According to this finding, digital twin technology has revolutionized the manufacturing and construction sectors by providing an innovative approach to system optimization and problem-solving. This technology provides virtual replicas of physical assets, processes, and systems, allowing for real-time monitoring and simulation. In the manufacturing sector, digital twins contribute significantly to smart manufacturing by enabling predictive maintenance, reducing downtime, and improving the overall efficiency of production lines. Meanwhile, in the construction industry, digital twins work seamlessly with Building Information Modelling (BIM) to provide detailed insights into the lifecycle of structures from design to operation. This will allow for more effective project planning, rapid prototyping, and enhanced collaboration among stakeholders. Through the integration of digital twins, both industries can analyze performance data, optimize designs, and make accurate decisions that lead to significant advancements in innovation.

Furthermore, this review also identifies significant research attention in areas such as maintenance, smart cities, and the emerging electric vehicle industry, implying a forward-thinking strategy for integrating digital twins into urban development and sustainable transportation. Despite the on-the-ground constraints and the need for cross-disciplinary collaboration, the academic has conducted considerable research on digital twins, from conceptual frameworks to practical implementations.

The enormous scholarly attention to digital twin research reflects the expected paradigm shift brought about by these technologies, which could enable groundbreaking future investigations that enhance efficiency and productivity across various industries. The positive academic discourse linked throughout the reviews is not only a testament to current achievement in digital twin technology but also a reflection of the direction these sectors are embracing. The publication trend indicates an emerging phase in which the virtual and physical worlds converge, promising innovative achievements that have the potential to transform the engineering and energy systems landscape.

Table 1. Digital twin review articles across industries

No.	Industry	Focus	Citation
1	General	Maintenance	[10] [11] [12] [13]
		Framework	[14]
		Mixed reality	[15]
		Safety	[16] [17]
2	Construction	Conceptual	[18] [19] [20]
		Application perspective	[5] [21] [22] [23] [22]
		Building information modelling (BIM)	[24] [5] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35] [27] [36] [37] [38] [39] [40]
		Building energy simulation (BES)	[41]
		Smart cities	[42] [43] [44]
		Safety	[45]
		Cyber-physical systems (CPS)	[21]
		Mixed reality	[19]
		Delay analysis	[46]
		Smart construction	[47]
		Smart monitoring	[48]
		Sustainable Design	[49]
3	Manufacturing	Application perspective	[50] [51]
		Smart manufacturing	[52] [53] [54] [55] [56] [57] [58] [56] [59] [60] [61]
		Cyber-physical systems (CPS)	[62]
		Cyber security	[63]
		Big Data	[64]
		Shop floor	[65]
		Maintenance	[66]
		Product engineering	[67]
		Non-destructive test (NDT)	[68]
		Sustainability	[69]
		Energy efficiency	[70]
		Industrial robot	[71]
		Remanufacturing	[72] [73]
		Welding	[74]
		Metallized film capacitor	[75]
4	Academic	Conceptual	[76] [77] [78] [79] [80] [81] [82]
		Application perspective	[83] [84][77] [85] [86] [87] [88] [89]
		Centrifugal valving	[90]
		Autonomous management	[91]
		Optical and wireless network	[92]

		Educational system	[93]
		Augmented reality	[94]
		Computing initiative	[95]
		Predictive maintenance	[96]
5	Power Generation	Carbon capture	[97]
		Power system	[98]
		Hydrogen	[99]
		Energy services	[100]
		Wind turbine	[101]
		Smart battery management	[102]
		Turbomachinery life cycle	[103]
		Sustainability	[104]
6	Oil and Gas	Application perspective	[6] [105]
		Air separation units (ASU)	[106]
		Virtual flow metering	[107]
7	Transportation	Shipping data modelling	[108]
		Internal transport systems	[109]
8	Automotive	Smart vehicle	[110]
		Electric vehicle	[111] [112] [113]
9	Software	Platform	[114]
		Autonomous management	[115] [115]
10	Agriculture	Augmented reality	[116]
		Smart farm	[117]
11	Supply Chain	Management	[118]
12	Sports	Physical activities	[119]
13	Water	Smart water grid	[120]
14	Mining	IoT	[121]
15	Chemical	Chemical process	[122]
16	Biopharma	Application perspective	[123]
17	Biomanufacturing	Mammalian cell culture	[124]
18	Healthcare	Application perspective	[44]

Table 2 summarizes the review study on digital twins in the power generation industry and identifies a significant gap: To date, no reviews have been published that specifically address power plant applications. This finding reveals a significant gap in collective academic understanding, encompassing both practical knowledge and methodological approaches in this field. In addition, the need for expanding knowledge in this area is highlighted by the growing urgency for industries to meet the goals set by the Conference of the Parties (COP) and adhere to environmental, social, and governance (ESG) standards, all within the larger framework of dealing with climate change. The researcher should perceive this gap as an opportunity to make a valuable contribution of new knowledge and insights, rather than as a setback. The study's findings have the potential to drive academic advancement and foster innovative approaches in power generation, motivating the researcher to implement significant changes in the industry.

Therefore, it is recommended that forthcoming studies lay the foundational work for an application taxonomy of digital twins within the context of power plants in addressing the emerging needs. This would encompass various perspectives, conceptual frameworks, potential challenges, and enablers that facilitate the seamless adoption of these advanced systems. The development of a roadmap for the evolution of digital twins in power plants is imperative, with a particular focus on elucidating publishing trends that will illuminate the path forward to unlock the full potential of digital twins in the power generation sector, as well as future research opportunities. As a result, the landscape of digital twin technology in the sector of power generation is ready for significant exploration and advancement. However, this study required the collaborative efforts of domain experts in the validation of relevant articles covering a wide range of power plant components and processes. Such interdisciplinary collaboration has the potential to significantly contribute to the field, resulting in increased publication trends and fostering a robust discourse about digital twin technologies in the power generation sector. With this collaborative spirit, the future research landscape appears substantial and promising, ready to support the transformative initiatives required for a sustainable and resilient energy future.

Table 2. Digital twin review articles across industries

No	Focus	Description	Method	Citation
1	Carbon Capture	Carbon dioxide transportation in carbon capture and storage system	SLR	[97]
2	Power System	Power System	Survey	[98]
3	Hydrogen	Hydrogen-based systems for integration of renewable energy	LR	[99]
4	Energy Services	Energy services that are based on intelligent recommendation systems	LR	[100]
5	Wind Turbine	Reliability analysis of offshore wind turbine support structure	LR	[101]
6	Smart Battery Management	Smart Battery Management Systems	LR	[102]
7	Turbomachinery	Life cycle perspective	LR	[103]
8	Sustainability	Sustainable energy industry for Solar and Hydrogen	LR	[104]

3. METHODOLOGY

This review article adopted a combination of a systematic review approach and thematic analysis to identify the application themes and challenges in developing the digital twin for a power plant. Besides that, feedback from domain experts is critical for validating research boundaries and clarifying the scope of the study. This feedback can help identify potential biases, limitations, and weaknesses in the research design, data analysis, and results. Managing the article data can be divided into three (3) main processes: systematic review, data crunching, and metadata analysis. It consists of data collection and analysis to evaluate the articles focusing on the power generation industry.

Meanwhile, the Mendeley databases and ATLAS ti software are used as tools for data crunching and metadata analysis. **Figure 1** depicts the flow of the filtration process for the literature review based on inclusion and exclusion criteria. The selection process of literature articles was performed according to several selection criteria, as follows: 1) publication from 2016 - 2021, 2) Have at least keyword(s) Digital Twin, and 3) Focus on power plants operation and maintenance.

Systematic review: The first stage is to conduct a systematic review of research articles by identifying the current state of academic insight on the application of digital twins in power plants. Published articles were extracted using "Digital Twin" and "Power Plant" keywords from the database. If the keyword used in this search only uses "Digital Twin," the articles' results will be a few thousand. However, after focusing the search strings on power plant applications, the results show a significant drop and more focus, thus proving that the subject is still new. The literature search was performed in the SCOPUS, Science Direct, and Mendeley databases. The search results came out with 40 articles from (SCOPUS), 140 articles from (Science Direct), and 14 articles from (Mendeley).

Data crunching: Next, the articles were uploaded to Mendeley for data crunching. The data crunching involves removing duplicate articles, updating the authors, and ensuring the metadata is correct. Domain expert feedback is required to validate the scope of the study, which focuses on power plant operation or maintenance. As a result, 169 articles were excluded due to their premature results and anecdotes or irrelevant to digital twin applications in power plants. Some of the articles were also incomplete, or the full articles were not accessible, or they had broken links or overlapped metadata. Hence, the total number of articles to be reviewed thematically is 25.

Metadata analysis: Finally, the metadata for all 25 articles were exported from Mendeley to ATLAS.ti as primary documents for literature mapping. Several groupings were automatically initiated in the code group based on the metadata established in Mendeley. Several criteria for classification were established from the document list, including the article author, year, country, objective, plant types, focus area, method, software, category, themes, and challenges. Then, the articles were analyzed according to the year they were published and the discussion pattern. The total number of articles finalized into final documents and coded in ATLAS.ti is 25. Later, the codes were grouped into several criteria to construct the literature review matrix table as a summary.

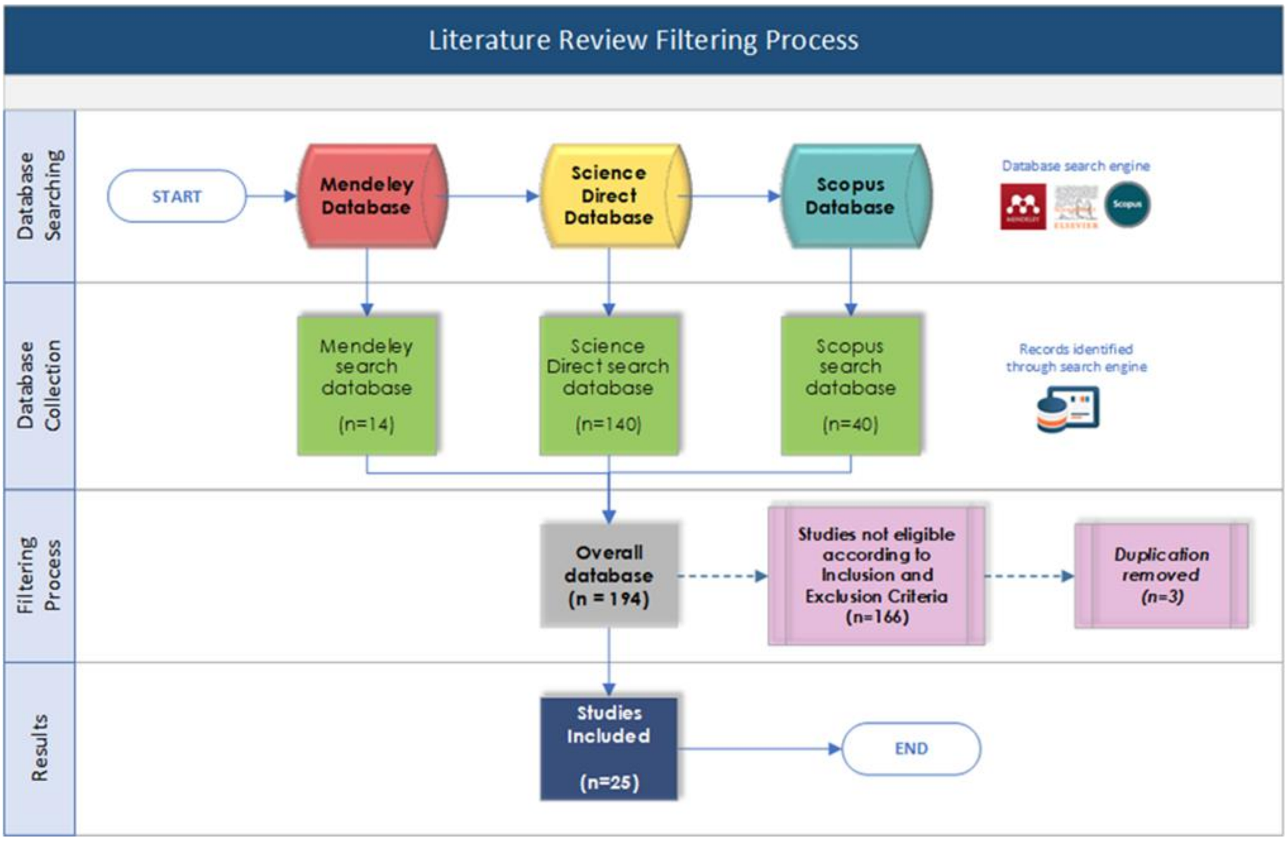

Figure 1. Literature review process flow

4. RESULTS AND DISCUSSION

The study's findings were examined from distinct viewpoints to validate the right direction to pave the future study. The details of these findings were organized according to twelve elements, as depicted in **Appendix A**: Literature review matrix analysis. The global trends of digital twin applications in power plants are presented in statistical form to visualize the recent direction of trends.

4.1 Word Cloud

The most prevalent words in this research area were discovered through keyword co-occurrence analysis. **Figure 2** depicts a word cloud generated from the 25 documents that captured the top four (4) terms 'System' which has been mentioned 3472 times, followed by 'model' was mentioned 3421 times. The presence of the words "System" and "Model" in the word cloud indicates the high frequency of the articles. In contrast, 'process' and 'maintenance' were mentioned 2158 and 1755 times. However, this analysis shows that 'operation' and 'real-time' words are not the top word cloud as the most popular topic. It is indicated that most researchers focus on the maintenance level rather than the operational level by using non-real-time data to validate the hypothesis. Thus, this absence can be considered a gap for future study exploration.

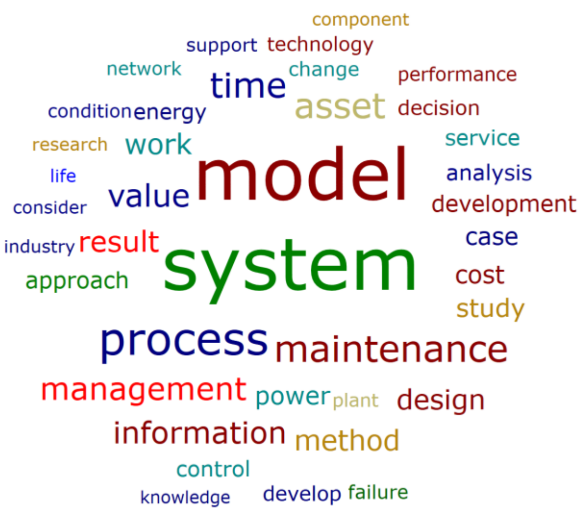

Figure 2. Word cloud generated from literature review articles.

4.2 Publication Statistic

Figure 3 illustrates the trend of articles throughout the six (6) years of publication in the databases. The trend of publications has increased significantly over the years. There has been a significant surge in publications from only one published in 2017 to 12 published in 2020 and still counting for 2021. The primary reason for this surge is driven by technological advancements in the recent 4IR era in data processing, storage, and transmission. Even though the trend is growing, no review paper discusses the integration and mapping of this strategy for the future.

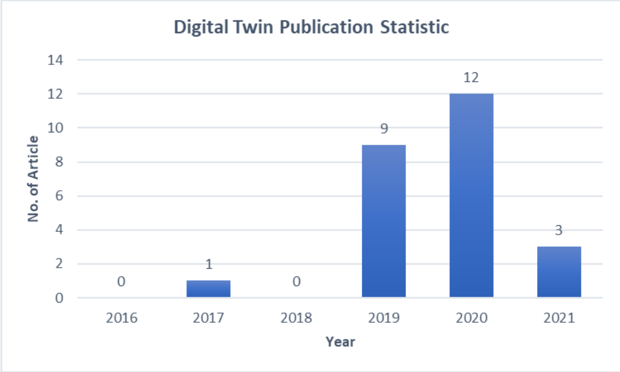

Figure 3. Articles trending according to the year of publication.

4.3 Application Themes

Figure 4 shows the pattern analyzed of themes established from the selected publications: Analytical solution (7), Engineering (11), Case study (9), and Training (1). The main themes are not independent but somewhat overlap between articles presented in this review, and it is common for some articles to adopt several themes and vice versa. The following section will discuss the theme to formulate the conclusion and recommendations for future studies.

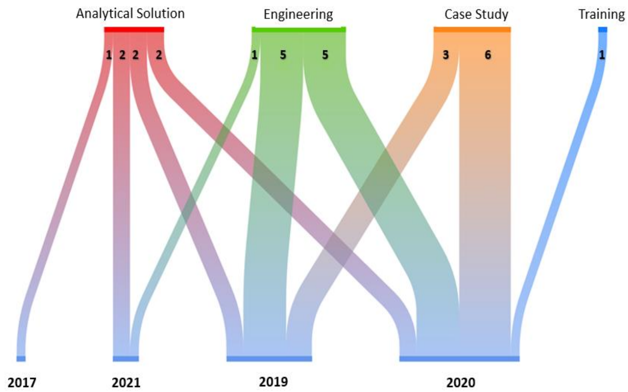

Figure 4. The theme according to publication year

4.4 Geographical Dispersal

The digital twin applications in power plants were more prevalent in developed countries such as Russia and China. **Table 3** indicates that Russia led the digital twin research primarily on engineering and case study applications. Besides that, digital twin publications are also reported from other countries, such as Germany, the United Kingdom, France, Iran, Malaysia, Poland, Portugal, the Republic of Korea, Singapore, South Africa, Tajikistan, and the UAE. This finding demonstrates that developed countries are at the leading edge of this research area due to established infrastructure and data availability. Another significant factor affecting the low number of published study articles is the limited access to plant data due to confidentiality and cybersecurity policies.

Table 3. The distribution of articles according to country and year

	2016	2017	2018	2019	2020	2021	Total
Russia	-	-	-	2	3	1	6
China	-	1	-	1	2	1	5
Germany	-	-	-	1	-	1	2
UK	-	-	-	1	1	-	2
France	-	-	-	-	1	-	1
Iran	-	-	-	-	1	-	1
Malaysia	-	-	-	-	1	-	1
Poland	-	-	-	1	-	-	1
Portugal	-	-	-	-	1	-	1
Republic of Korea	-	-	-	-	1	-	1
Singapore	-	-	-	1	-	-	1
South Africa	-	-	-	-	1	-	1
Tajikistan	-	-	-	1	-	-	1
UAE	-	-	-	1	-	-	1

4.5 Development Analysis

This section examines global trends in developing digital twin applications for power plants. Digital twins are virtual replicas of physical assets, systems, or processes that allow simulation and analysis of their behavior and performance in a virtual environment. The classification of the development approach is divided into three main sections: method, software, and target. **Figure 5** shows the information mapping to understand the different approaches, tools, and applications in developing digital twin technology.

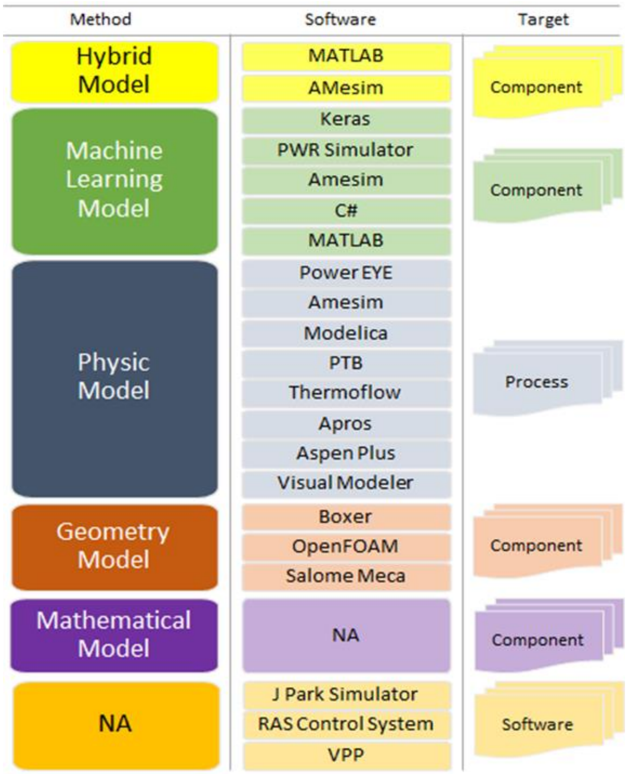

Figure 5. Digital twin development approach and software

The method section refers to the different approaches or techniques to develop digital twins. In this study, there are five approaches identified for developing digital twins: hybrid model, machine learning model, physical model, geometry model, and mathematical model. The following is the overview of five approaches identified in this study:

a. **Hybrid model**: This approach combines different modeling techniques, such as physical and mathematical models or data-driven and physical models, to create a more comprehensive digital twin.
b. **Machine learning model**: This approach uses machine learning algorithms to analyze data from the physical system and create a digital twin that can predict the system's behavior and performance.
c. **Physical model**: This approach involves creating a digital twin that directly replicates the physical asset, system, or process using CAD (computer-aided design) software or other modeling tools.
d. **Geometry model**: This approach creates a simplified version of the physical system that focuses on the system's geometry, such as the shape, size, and position of the components.
e. **Mathematical model**: This approach uses mathematical equations and models to represent the behavior and performance of the physical system in a digital twin.

Next, the software section refers to the tools and technologies used to develop digital twins, such as modeling software, simulation tools, and data analytics platforms. The choices of software or tools used will depend on the development approach, target application, and other factors. A brief description of each software and tool is shown in **Table 4**.

Table 4. List of tools and description

No	Tools	Description
1	MATLAB	A numerical computing environment and programming language can be used for data analysis, visualization, and modeling.
2	AMesim	Simulation software can be used to create models of physical systems and components.
3	Keras	A deep learning framework that can be used to develop machine learning models for digital twins.
4	C#	A programming language that can be used to develop software applications for digital twins.
5	PowerEye	A software tool that can be used to develop digital twins of power systems and energy assets, including wind turbines and solar farms.
6	Modelica	An object-oriented language for physical systems modeling that can be used to create digital twins.

7	PTB	A software tool for modeling and simulation that can be used in industrial processes and systems.
8	Thermoflow	A software tool for designing and simulating that can be used in energy systems such as power plants, refrigeration systems, and HVAC systems.
9	Apros	A software tool for dynamic simulation of processes and power plants.
10	Aspen Plus	Process simulation software can model chemical processes, including chemical reactions and thermodynamics.
11	Visual Modeler	A modeling software tool that can be used to create digital twins of complex systems, including aerospace and defense systems.
12	Boxer	A simulation software tool that can be used to create digital twins of mechanical systems, including robots, vehicles, and machines.
13	OpenFOAM	An open-source computational fluid dynamics (CFD) software tool that can be used to simulate fluid flows and heat transfer.
14	Salome Meca	A software tool that for multi-physics simulations of mechanical and thermal systems.

Finally, the target section refers to the specific application or purpose of the digital twin, such as predictive maintenance, optimization, or monitoring. The scope of the study can be categorized into three focus areas: component, process, and software. This study found a lack of studies on the machine learning method, as it primarily focuses on the component rather than the process level. The scope of the component study focuses on various types of power plants, including nuclear plants, gas turbines, coal-fired plants, renewable energy, and general components.

This review suggests that future studies should leverage the advantages of the IR4.0 technology revolution by focusing on machine learning methods to develop power plant anomaly detection and performance monitoring for process applications. The machine learning approach is crucial as it allows for better accuracy and precision in predicting power plant performance and detecting anomalies. The advancement of technology in the era of IR4.0 should be aligned with the development approach to developing an effective and efficient digital twin platform. Future studies should focus on utilizing machine learning methods and IR4.0 technology to enhance the development of digital twins for power plant applications. It can be done by utilizing new tools and techniques to improve performance, increase efficiency, and reduce costs. This analysis highlights the importance of considering the latest technological advancements while developing digital twin applications for power plants.

5. CHALLENGES AND ENABLERS

This section will discuss the findings obtained from the current publication to establish the relationship between the challenges and enablers. The scope of analysis is divided into three (3) steps: 1) Challenges Identification, 2) Enabler Identification, and 3) Connecting challenges and enablers. This analysis examines the challenges authors faced during the research process and identifies other factors that facilitated or supported the research. It can also help identify potential biases or limitations in the reviewed literature and identify areas where additional support or resources may be needed to advance the research agenda. Enablers in challenges might include funding, access to resources or collaborators, or technological advances that enable more complex or sophisticated research methods. However, this study will examine the correlation between IR4.0 elements as enablers and identified challenges. At the end of this section, the application conceptual framework is constructed based on current findings to deepen the research area.

5.1 Challenges Identification

The challenges identified in the current publication were organized according to functionality, types of plants, and category. **Table 5** shows the details of the challenges classification based on above mentioned criteria. The digital twin applications in power plants can be grouped into seven (7) study majors: anomaly detection, performance monitoring, data security, engineering, environment, energy management, and training. Anomaly detection is recorded as the most popular topic of study, followed by performance monitoring and data security. Meanwhile, coal-fired, and gas-turbine plants dominate the most prevalent study on power plant types.

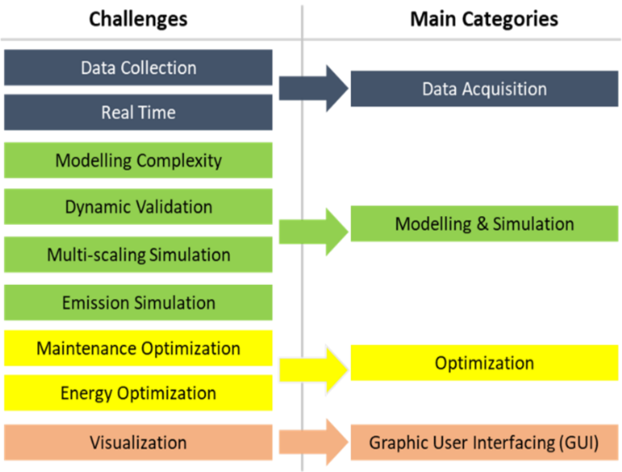

Figure 6. Challenges classification based on main categories.

In 2022, Perno et al. [125] highlighted several barriers to digital twin applications in the process industry. However, the outcome of this study is inadequate as it provides a general review which is unable to address fundamental issues in the power generation industry. Therefore, this study performs a specific review of digital twin applications in power plants. This study found that numerous challenges have been discovered in the digital twin publication for power plant applications. The findings have concluded that the challenges can be classified into nine (9) categories: modeling complexity, dynamic validation, data collection, real-time, multi-scaling simulation, maintenance optimization, visualization, emission simulation, and energy optimization. Later, these categories are grouped into four main categories, as shown in **Figure 6**: data acquisition, modeling and simulation, optimization, and graphic user interfacing (GUI). Addressing these challenges requires collaboration between experts in various fields, including plant design, simulation, data analytics, and environmental science. In addition, ongoing investment in research and development is necessary to improve the accuracy and reliability of digital twin technology in power plant applications.

Table 5. The challenges classification based on the digital twin function.

No.	Function	Author	Plant	Challenges	Category
1	Anomaly Detection	[126]	Nuclear	Modeling for Complex object	Modeling Complexity
		[127]	Hybrid	Component maps modeling	Modeling Complexity
		[128]	Gas Turbine	Modeling for Complex object	Modeling Complexity
		[129]	Coal Fired	Combustion behavior for different grate firing systems	Modeling Complexity
		[130]	RE (Hydro)	Accuracy of turbine and generator modeling	Modeling Complexity
		[131]	RE (Wind)	Validation of dynamic behavior of the pitch angle control	Dynamic validation
		[132]	General	Vibration data gathering and analysis	Data Collection
		[133]	Nuclear	Maintenance data captured for dynamic behavior	Data Collection
		[134]	General	Consistency of virtual and real systems during a real-time interaction	Real-time
		[135]	Gas Turbine	Hybrid approach in real-time	Real-time
		[136]	Gas Turbine	Simulation scaling and data-driven feedback	Multi-scaling Simulation
		[137]	Gas Turbine	Strategic economic decisions	Maintenance Optimization
2	Process Validation	[138]	Gas Turbine	Mathematical modeling for components and elements	Modeling Complexity
		[139]	RE (Wind and Hydro)	Modeling strategy for electromagnetic, mechanics, and thermal	Modeling Complexity
		[140]	Coal Fired	Accuracy - Model calibration within 5 % error	Modeling Complexity
		[141]	Coal-fired	Off-design and dynamic operation	Dynamic validation
		[142]	Co-gen (Coal Fired)	Plant impacts under the high frequency of load variation	Dynamic validation
		[143]	Coal Fired	Oxy combustion dynamic modeling and control strategies	Dynamic validation
		[144]	Coal Fired	Plant monitoring and storage by remote	Visualization
3	Data Security	[145]	Nuclear	Plant modeling development	Modeling Complexity
		[146]	Nuclear	Flexible modeling to validate life cycle	Dynamic validation

4	Engineering	[147]	Nuclear	FEM development as per visualization data	Modeling Complexity
5	Environment	[148]	General	Limited boundary for a software agent to simulate a function	Emission Simulation
6	Energy Management	[149]	General	Demand response estimation	Operation Optimization
7	Training	[150]	General	Process control validation in dynamic operation	Dynamic validation

5.1.1 Data Acquisition

The first challenge in developing a digital twin is data acquisition which consists of a data collection process and real-time data streaming. Data acquisition in a power plant involves the process of measuring and recording real-world physical conditions using sensors, measurement devices, and a computer. The collected data is converted into digital numeric values that can be processed and analyzed. It is a critical aspect of the data collection process in power plants. Meanwhile, data streaming involves continuously transferring real-time data to a central system for analysis and processing. It allows real-time plant operations monitoring and provides an early warning system for potential issues.

Data Collection: Digital twins require vast amounts of data from various sources, such as sensors, control systems, and operational records, to create an accurate representation of the physical system. The information gathering can be done via offline or online approaches. These approaches allow researchers to start a journey in this study area. With the recent advancement of technology in 4IR, an online approach should be available across the power plant control system to enable system integration with third-party access. However, upgrading the legacy control system to communicate with new technology requires high investment. This statement is supported by Wishnow et al. [1] on the fundamental issues of system integration in the oil and gas industry, which require significant investment and extended production downtime due to the transition of aging control systems.

Real-Time: The system integration provides significant advantages to a researcher to deepen the study in this area as the plant information can be accessed in real-time. Real-time data access is gathering and analyzing data in real-time, allowing for immediate insights and decision-making based on current conditions. It requires high performance of hardware and software to exchange information efficiently from the physical to digital twin and vice versa. Traditionally, plant owners will invest highly to establish the infrastructure and resources. However, this approach should be changed as the plant owner should migrate from capital expenditure (CAPEX) into operational expenditure (OPEX) with significant cost savings. Nowadays, many vendors in the market have offered cloud services and storage systems, which only require less cost for subscription. Another challenge in real-time data streaming is limited access for cyber security reasons. Several authors have highlighted this issue: Xia et al. [151] ; Redelinghuys et al. [4] ; Zhang et al. [3] on big data access and processing in real-time for general industrial applications. In addition, most power plants today are subjected to cybersecurity compliance governed by ISO27001 standards to foresee the three (3) essential elements: confidentiality, integrity, and availability. Hence, implementing this standard becomes the main obstacle in the digital twin development process due to restricted access and cybersecurity reasons.

5.1.2 Modelling and Simulation

The second challenge in creating a digital twin is plant modeling and simulation. A digital twin must accurately model the physical system to represent the system's behavior accurately. However, developing an accurate and reliable plant model can be challenging, particularly for large and complex systems. The model must account for the behavior of all system components, including their interactions and dependencies. Additionally, the model must be validated and calibrated to ensure that it accurately reflects the behavior of the physical system. This section will discuss the four subcategories: modeling complexity, dynamic validation, multi-scaling simulation, and emission simulation.

Plant Model Complexity: Power plants are complex systems with many interdependent components and processes that must be modeled accurately to create a practical digital twin. Accurately modeling the behavior of these components and processes requires a deep understanding of the plant's physical and operational characteristics and the ability to incorporate real-time data from sensors and other sources. Developing an accurate and reliable plant model can be challenging, particularly for large and complex power plants.

Dynamic Validation: A digital twin must be continuously validated to ensure that it accurately reflects the behavior of the physical system. This approach is particularly challenging in power plants, which operate in a constantly changing environment with inputs such as fuel quality, ambient temperature, and electricity demand changing frequently. Ensuring the digital twin remains accurate and up to date in this dynamic environment is a significant challenge. Dynamic validation requires real-time data monitoring, modeling, and simulation, which can be computationally intensive and require advanced analytics capabilities.

Multi-scaling Simulation: Power plants operate at different scales, from the individual component to the plant-wide level. To accurately simulate the behavior of a power plant, a digital twin must incorporate models at multiple scales. Developing and integrating these models can be challenging because they may have different levels of complexity and require different computational resources. Ensuring that the models are consistent across different scales and accurately capture the behavior of the physical system can be a significant challenge.

Emission Simulation: The power plant is a significant source of greenhouse gas emissions, requiring environmental impact analysis to evaluate the current conditions. In general, emission monitoring in power plants can be categorized into continuous emission monitoring systems (CEMS) and predictive emission monitoring systems (PEMS). The selection of these methods depends on operating and maintenance costs, reliability, and system independence. However, PEMS is the most popular method of emission monitoring systems using software-based calculations compared to hardware-based in CEMS. It is critical in predicting and simulating gas emissions because it requires accurate modeling of combustion processes and the behavior of pollutants in the atmosphere. The accuracy of emission simulation depends on the quality and availability of data on fuel composition, combustion efficiency, and other factors that can vary widely across different power plants.

5.1.3 Optimization

Developing digital twin applications for power plant maintenance and operation optimization is complex. These areas of study strongly correlate with each other; for example, the predictive maintenance interval results from the operation regime and operating variables. Hence, the researcher needs collaboration with technical experts to understand each component's working principle and the power plant's process behavior. Besides that, this study has identified several key factors associated with implementing digital twins for optimization: data availability and quality, interoperability, model complexity and validation, simulation accuracy, analytical tools, and cyber threats. By overcoming these factors, plant personnel can optimize plant performance, reduce downtime, and improve efficiency, leading to cost savings and increased profitability.

Data Availability and Quality: Digital twins must be fed high-quality data from various sources such as sensors, DCS, SCADA, operational records, and maintenance logs. However, data quality and availability can be challenging, particularly for older power plants or plants with legacy systems. It is due to the lack of standardization, data silos, and the large volumes of data generated by the assets. Gathering, integrating, and interpreting this data to build a comprehensive digital twin model might be challenging. In some cases, data may not be available or incomplete, making it challenging to develop accurate models for optimization. Hence, implementing a digital twin optimization system can be costly, particularly for older power plants that may require upgrades to sensors and control systems. The benefits of digital twin optimization, such as improved maintenance and energy efficiency, must be weighed against the costs of implementing and maintaining the system over time.

Interoperability: Digital twin platforms should be able to interface and integrate with multiple data sources systems. Integrating digital twins into existing systems can be challenging, as it must be seamlessly integrated with control systems to archive databases and deploy analytics tools. This integration requires a deep understanding of the existing infrastructure, and any changes must be made with minimal disruptions to ongoing operations. Moreover, disparate data sources may use different data formats and provision access levels and may not be compatible.

Model Complexity and Validation: Digital twin optimization systems must be based on accurate and reliable plant models that capture the complex interrelationships between various plant components and operational parameters. Developing and validating these models can be challenging, particularly for large and complex power plants. Ensuring that the models remain accurate over time requires ongoing validation and calibration.

Simulation Accuracy: The accuracy of the digital twin model is critical in ensuring that the model accurately represents the behavior of the physical asset. Any errors or discrepancies in the model can lead to incorrect predictions and poor performance and maintenance decisions. The digital twin model needs to simulate the behavior of the plant accurately, considering various operating conditions and scenarios. These models must also be continuously updated with the latest data to ensure their accuracy and reliability.

Analytical Tools: The digital twin application is used to predict equipment failures and other issues before they occur, allowing plant operators to take preventive action. This approach requires advanced analytics and machine learning algorithms that can identify patterns and anomalies in the data and provide predictive insights. Moreover, this tool should be able to optimize plant operations to improve efficiency and reduce downtime. It requires the application to analyze data in real-time, identify opportunities for optimization, and provide recommendations to plant operators.

Cyber Threats: Digital twins rely on data from various sources, including sensors, IoT devices, and other systems, which can pose security and privacy risks. It is mandatory to ensure that appropriate security and privacy measures are in place to protect sensitive data and prevent cyber-attacks. In addition, protecting against cyber threats requires ongoing monitoring and security updates and regular cybersecurity training for plant personnel.

5.1.4 Graphic User Interfacing (GUI)

The large volume of data generated by the sensors is a major factor in the need for effective visualization systems for plant operators to process and analyze plant data in real time, which can be challenging without the right tools and technologies. However, the rise of the IR4.0 application has become increasingly popular in recent years, enabling plant personnel to monitor plant operation and performance in real time. Developing effective visualization systems is a critical challenge when building digital twins for power plants, as each power plant has unique operating conditions and configurations an effective visualization is essential as it provides an intuitive representation of the data collected from the sensors installed on the plant equipment, allowing operators to identify any issues and take corrective action quickly. Several challenges have been identified in developing an effective visualization system for power plant monitoring.

The visualization system needs to be designed to meet the specific needs of the plant operators, be scalable and adaptable, and provide an intuitive representation of the data collected from the plant equipment. Moreover, the visualization system needs to adapt and provide accurate real-time monitoring as the plant equipment ages; new sensors are installed, and the plant's performance changes. Overcoming these challenges can help plant operators optimize the plant's performance by improving overall efficiency, reducing downtime, and improving the reliability of the plant. Advanced data analytics can be used to enhance the visualization system to become a user-friendly interface.

5.2 Enabler Identification

The fourth industrial revolution (4IR) has brought significant change in the manufacturing industry, with the widespread adoption of advanced technologies such as digital twins. In the power generation industry context, the eleven (11) pillars of 4IR in smart manufacturing technologies were evaluated to address the challenges in developing the digital twin for power plants. **Figure 7** shows the eleven (11) pillars of 4IR technology advancement. However, this study has identified the eight (8) pillars that can be adopted as enablers to facilitate the successful implementation of digital twin applications in power plants: System Integration, Cybersecurity, Big Data, AI, IoT, Cloud, Simulation, and VR/AR. These elements have been chosen as enablers based on the outcomes of challenges in developing digital twin applications for power plants.

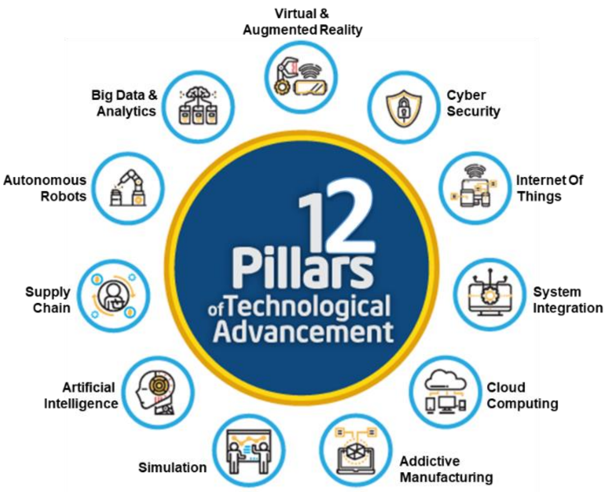

Figure 7. Eleven Pillars of 4IR technology advancement

5.2.1 System Integration

Integrating digital twin systems with power plant control systems is vital for seamless communication and data exchange between the digital twin and processes in power plants. Several communication platforms can be integrated to empower the digital twin system, including smart sensors, cloud computing, and 5G communications. The industrial control system generally has open platform communication (OPC) features to enable third-party data access and communication interoperability. OPC unified architecture (UA) is a widely accepted standard for plant systems integration, which incorporates three essential elements such as data access (DA), alarms and events (AE), and historical data access (HDA). By integrating digital twin systems with existing plant systems and processes, operators can monitor plant performance in real-time and make firm decisions to optimize plant performance.

5.2.2 Cybersecurity

Cybersecurity is critical to protecting digital twin technology in power plants from cyber threats, as it ensures data confidentiality, integrity, and availability. The policy maker and regulatory bodies play a leading role in strengthening cybersecurity resilience across various sectors and implementing robust security measures to protect the power grid and energy infrastructure from cyber threats. Some basic cybersecurity measures include using secure passwords, regularly updating software and applications, and using firewalls and intrusion detection systems. It is crucial to use cybersecurity measures tailored to the power plant's specific needs and its digital twin system and to stay up to date with the latest threats and security technologies. By following best practices and continuously improving cybersecurity, power plants can protect their digital twin systems from cyber threats and ensure optimal performance and operation.

5.2.3 Big Data

Big Data is a term that refers to large, complex datasets that are difficult to process using traditional data processing techniques. It has become an essential tool for businesses and industries that generate vast amounts of data, including power plants. By capturing and analyzing large volumes of data generated by the power plant, big data can provide insights critical to optimizing plant performance, identifying patterns and trends, and predicting and preventing potential issues. In the context of power plants, big data can help operators identify inefficiencies in plant operations and reduce costs associated with maintenance and repairs. Additionally, big data analytics can help predict and prevent equipment failures before they occur, reducing downtime and improving overall plant reliability.

However, handling big data can be challenging and requires powerful computational resources and specialized expertise. To effectively leverage big data, power plants may need to invest in sophisticated data management and analysis tools and training for employees to understand and interpret the results. In conclusion, big data presents many opportunities for power plants, requiring a significant investment in resources and expertise to be effectively utilized. With the right tools and training, however, power plants can unlock the full potential of big data to improve plant operations, reduce costs, and enhance overall efficiency.

5.2.4 Artificial Intelligence (AI)

Artificial Intelligence (AI) has revolutionized the world of data analytics and predictive modeling, making it possible for operators to make informed decisions and optimize plant performance. AI has many applications in the power plant industry, including machine learning algorithms that can automatically detect anomalies, predict equipment failures, and identify optimal operating conditions. For example, AI techniques are used in the financial sector to identify fraudulent transactions, fast and accurate credit scoring, and automate manual data management tasks. In addition, AI is streamlining the data analytics process, making it less labor-intensive and automating intelligent bots and algorithms that learn from vast data sets to make automated, more intelligent decisions. AI in the power plant industry can also help identify patterns and trends, optimize plant performance, and predict and prevent potential issues by analyzing large volumes of data generated by the power plant. By leveraging AI and developing advanced analytics and predictive models, power plant operators can make data-driven decisions, achieve higher levels of efficiency, and reduce costs associated with maintenance and repairs. Thus, AI is an essential tool for power plants looking to stay ahead in the industry and ensure optimal performance.

5.2.5 Internet of Things (IoT)

It is a network of interconnected devices equipped with sensors, software, and connectivity capabilities to collect and exchange data over the internet. IoT has gained significant attention and is transforming various industries due to its potential to enhance efficiency, improve decision-making, and enable new services and business models. The widespread adoption of IoT is driven by its potential to revolutionize various aspects of our lives and drive innovation across multiple sectors. Some of IoT's notable applications are as follows: industrial automation, predictive maintenance, supply chain optimization, Smart Grids, Energy Management, and Transportation and Logistics. In terms of its fundamental aspects, IoT relies on three key components: devices and sensors, connectivity, and data processing and analytics.

a. **Devices and Sensors:** IoT devices have sensors and actuators that gather data from the environment or perform actions based on the received instructions. These devices can collect information such as temperature, humidity, location, motion, and vice versa.
b. **Connectivity:** IoT devices are connected to the internet or other networks, enabling them to communicate with other devices and central systems. This connectivity can be achieved through various means, including Wi-Fi, cellular networks, Bluetooth, and low-power wide-area networks (LPWANs).
c. **Data Processing and Analytics:** The data collected from IoT devices is processed, analyzed, and transformed into meaningful insights. This process involves applying advanced analytics techniques like machine learning and artificial intelligence to derive valuable information from the collected data.

5.2.6 Cloud

Cloud computing is a technology that allows users to store, access, and process data through remote servers connected to the internet. Cloud technology provides a secure and scalable platform for storing and processing data generated by the digital twin in the context of a power plant. The digital twin is a virtual model that simulates the performance of physical assets and systems in real-time. Storing data generated by the digital twin in the cloud allows power plant operators to access and analyze data from anywhere and at any time, making it easier to identify and respond to issues quickly. In addition, cloud storage is a cloud computing model that enables storing data and files on the internet through a cloud computing provider that can be accessed through the public internet or a dedicated private network connection. This model has become increasingly popular as it moves expenses from a capital expenditure (CAPEX) model to an operational expenditure (OPEX) model. It can be accessed through the public internet or a dedicated private network connection, and it allows data and files to be stored in an off-site location, making it the responsibility of a third-party cloud provider. In conclusion, cloud storage is an efficient and cost-effective way for power plant operators to store and access data generated by the digital twin, and it allows them to respond to issues and make firm decisions quickly.

5.2.7 Simulation

Simulation is a powerful tool that enables power plant operators to simulate different scenarios and test different strategies in a virtual environment. Operators can identify potential problems and optimize plant performance without costly and time-consuming physical tests. With simulation, operators can explore various possibilities and better understand how their power plant operates under different conditions. This platform allows them to make informed decisions and take proactive steps to improve the efficiency and reliability of their plant. Additionally, simulation can be used to train operators and engineers, allowing them to gain valuable experience and develop the skills they need to manage and maintain the plant effectively. Overall, simulation is a critical tool for power plant operators, as it helps them to reduce costs, improve performance, and ensure the safety and reliability of their plants.

5.2.8 VR/AR

Virtual Reality (VR) and Augmented Reality (AR) technologies have gained popularity recently and are now used in various fields. VR and AR provide an immersive and interactive way to visualize and interact with the digital twin, a virtual replica of a physical asset of the power plant. This method can help power plant operators better understand the plant's operations, identify potential issues, and test new ideas as solutions.

Furthermore, by using VR and AR applications, operators can experience a virtual walkthrough of the power plant, thoroughly investigating the various components and systems. Besides that, the plant data can be visualized in real-time, allowing them to spot patterns and trends that traditional data visualizations may not reveal. The hybrid approach will assist plant personnel in identifying potential problems and opportunities for optimization promptly. Moreover, this application also can be utilized to test new ideas and solutions, allowing them to assess their effectiveness before execution in the physical plant quickly. Overall, VR and AR applications can provide an immersive and interactive way for power plant operators to visualize, analyze, and optimize the plant's operations effectively.

5.3 Connecting Challenges and Enablers

This section will discuss the connection of eight (8) key pillars of the Fourth Industrial Revolution (4IR) and their role as enablers in addressing challenges in developing digital twin technology for power plants. These pillars are crucial components contributing to the advancement and successful implementation of digital twins in the power plant industry. The connection between the challenges and enablers is shown in **Table 6**. The eight (8) key pillars of 4IR are connected to respective challenges to deploy a primary function in the proposed operating platform. The proposed operating platform introduces four (4) platforms: communication platform, simulation platform, optimization platform, and monitoring platform. These platforms serve as the infrastructure for integrating the identified enablers with the challenges associated with digital twin development for power plants. It is derived from the relationship of enablers and challenges under the operational ecosystem for digital twin development. The user can effectively manage the challenges and empower enablers via this platform by understanding the operational ecosystem.

The communication platform plays a significant role in addressing data collection methodology and real-time data management issues. It enables effective data gathering and management strategies to ensure accurate and timely information for digital twin applications. The 4IR pillars that can serve as enablers for the communication platform include IoT, Cybersecurity, System Integration, and Cloud. These technologies provide the tools and frameworks to support seamless data exchange, secure communication, and efficient integration of various systems and devices. By leveraging the communication platform, power plant personnel can establish robust data collection processes that capture essential information from various sources within the plant environment.

Meanwhile, the simulation platform addresses four challenges: complex modeling, multi-scaling, dynamic validation, and emission prediction. Through this platform, plant operators and engineers can create virtual models replicating real-world scenarios, allowing them to understand better and optimize the plant's performance. The simulation platform benefited from the 4IR pillars, such as Big Data, AI, VR/AR, Simulation, and Cloud. These technologies lead to accurate predictions and analysis by providing advanced data analysis, artificial intelligence algorithms, immersive visualization, and efficient utilization of computational resources.

Table 6. The Connection between Challenges and Enablers

No	Function	Challenges	IR 4.0 Enabler	Platform
1	Anomaly detection	Modelling Complexity	Big Data, AI, VR/AR	Simulation
		Dynamic Validation	AI, Simulation, Cloud	Simulation
		Data Collection	IoT, Cybersecurity, System Integration, Cloud	Communication
		Real-time	Cybersecurity, System Integration, Cloud	Communication
		Multi-scaling Simulation	AI, Simulation, Cloud	Simulation
		Maintenance Optimization	Big Data, AI, Simulation, Cloud	Optimization
2	Process Validation	Modelling Complexity	Big Data, AI, VR/AR	Simulation
		Dynamic Validation	AI, simulation, Cloud	Simulation
		Visualization	Cybersecurity, System Integration, Cloud	Monitoring
3	Data Security	Modelling Complexity	Big Data, AI, VR/AR	Simulation
		Dynamic Validation	AI, simulation, Cloud	Simulation
4	Engineering	Modelling Complexity	Big Data, AI, VR/AR	Simulation
5	Environment	Emission Simulation	Big Data, AI, Simulation, Cloud	Simulation
6	Energy Management	Operation Optimization	Big Data, AI, Simulation, Cloud	Optimization
7	Training	Dynamic Validation	AI, simulation, Cloud	Simulation

However, advanced applications such as performance optimization should be done in an optimization platform. This platform shall be equipped with optimization algorithms and techniques to solve optimization issues in operation and maintenance. Therefore, the simulation and optimization platform are proposed to merge into the unified application platform to link the plant model simulation and optimization algorithms. The unified application platform represents the integration of the platforms mentioned above into a comprehensive solution for digital twin development in power plants. This platform leverages the 4IR pillars, including Big Data, AI, VR/AR, Simulation, and Cloud, as enablers to support various applications and functionalities. By combining the capabilities of these pillars, the unified application platform provides a holistic approach to digital twin implementation, facilitating enhanced operational efficiency and decision-making in power plants.

Finally, the monitoring platform is proposed to address visualization issues in digital twin development. It utilizes the 4IR pillars of Cybersecurity, System Integration, and Cloud as enablers for effective remote monitoring capabilities. These technologies ensure secure data transmission, seamless integration of monitoring systems, and remote access to real-time plant data, enabling efficient monitoring and control of power plant operations.

6. CONCLUSION

This study has found eight (8) enablers from 4IR pillars that can be applied to address nine (9) challenges in developing the power plant digital twin. The eight (8) key pillars of the 4IR, including IoT, Cybersecurity, System Integration, Cloud, Big Data, AI, Simulation, and VR/AR, play essential roles as enablers in developing the power plant's digital twin technology. These pillars are incorporated into dedicated platforms to expedite development by resolving challenges with new approaches. This approach will contribute to the successful implementation of digital twins in the power plant industry.

Furthermore, the operational ecosystem has been constructed as the proposed conceptual framework to locate the challenges and apply the enablers at the right platform. **Figure 8** shows the operational ecosystem model derived from the multi-platform interaction of challenges and enablers. Initially, this framework consists of four (4) operational platforms: Communication, Simulation, Optimization, and Monitoring. The simulation function can perform a multi-purpose function, relying on digital twin modeling. Meanwhile, the optimization platform requires specific algorithms to perform optimization functions. However, in real applications, these functions should be interacted with each other as complementary to perform the decision-making. Therefore, the simulation and optimization functions were merged into a unified application platform. Finally, the operational platform is reduced from four (4) platforms to three (3) platforms.

The significance of system integration and cybersecurity pillars has been identified as crucial factors in communication and monitoring platforms. Integrating the system will facilitate the data linkage protocol between two distinct systems, enabling communication and visualization of the process data. The distributed control system (DCS) data is vulnerable to cyber threats and unauthorized access. However, the double cybersecurity protection from front to end may pose difficulties for cyber threats to access the DCS. Contrarily, applying cybersecurity protection to the application platform is not advisable as it may lead to reduced hardware performance and slower application response. In addition, unidirectional data transport is recommended for the primary data analytics function.

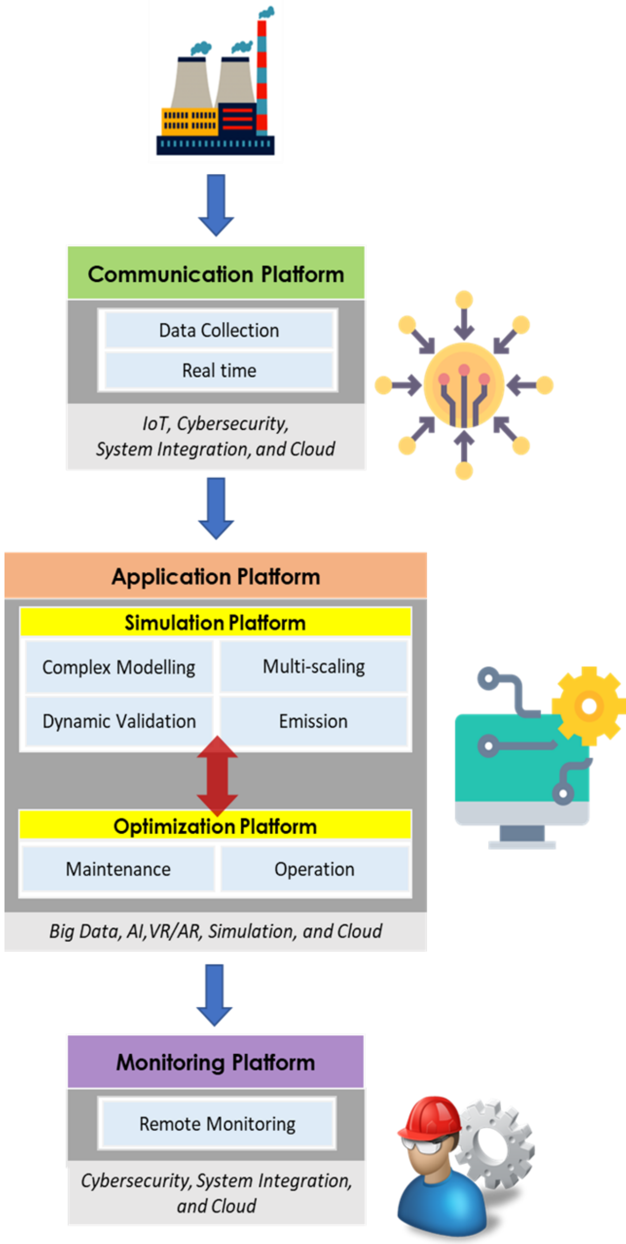

Figure 8. Proposed digital twin operational ecosystem model for power plant application.

In contrast, an advanced application requires bidirectional data transport to collaborate with DCS to update the optimization function block in real time. Collaboration with DCS makers is necessary to allow some essential input from third-party applications to access the control logic environment. The central infrastructure must have a high-speed data connection and high-performance hardware to process the data in real-time.

Moreover, this study also found that cloud technology plays a significant role in providing a holistic solution as it can be applied across the operational ecosystem. The plant personnel should consider leveraging this technology in developing a power plant digital twin at optimum cost. This technology offers fewer expenses and provides greater flexibility for operational and maintenance activities. The plant owner will benefit from a new financial model to utilize the digital twin without owning the hardware infrastructure. Hence, the capital expenditure (CAPEX) model is expected not to be valid in the future as the user can be more selective of service providers, which leads to competitive operational expenditure (OPEX). This landscape will increase the demand for cloud technology and create more growth opportunities for this industry.

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APPENDIX

Literature review matrix analysis

Authors	Country/ Year	Focus	Plant	Method	Software	Theme	Challenges
[126]	China 2021	Fault diagnostic for anomaly monitoring	Nuclear	CGRU and EPSO	PWR Simulator	Analytical	Complexity of object modelling
[127]	UK 2020	Health monitoring for transient operation	Hybrid GT & Wind	Machine Learning	-	Analytical	Component maps modelling
[137]	UAE 2019	Predictive maintenance	Gas Turbine	Physic Model	Power Eye	Analytical	Strategic economic decisions
[132]	China 2017	Life prediction	General	Deep Learning	Keras	Analytical	Vibration data gathering and analysis
[152]	Russia 2021	Failure identification and prediction	Gas Turbine	ANN	-	Analytical	Complexity of object modelling
[135]	Russia 2019	Condition monitoring for maintenance	Gas Turbine	ANN, Physic Model	Amesim	Analytical/ Engineering	Hybrid approach in real-time
[153]	Korea 2020	Anomaly detection and health monitoring	Nuclear	PCA, k-Means, SVM	-	Analytical	Maintenance data captured for dynamic behaviour.
[138]	Russia 2019	Performance monitoring and improvement	Gas Turbine	Physic Model	Modelica	Engineering	Mathematical modelling for components and elements
[154]	Singapore 2019	Emission conceptual framework	General	-	J-Park Simulator	Engineering	Limited boundary for software agent to simulate a function
[146]	Russia 2020	Operators Support system to enhance cybersecurity and reliability	Nuclear	-	ICS RAS Control System	Engineering	Flexible modelling to validate life cycle
[145]	Russia 2020	Flexible modelling software package development	Nuclear	-	-	Engineering	Plant modelling development
[149]	Portugal 2020	Distributed Energy management framework	General	-	Virtual Power Plant	Engineering	Demand response estimation
[139]	Germany 2019	Generators modelling	RE Wind and Hydro	Multi-Physic Model	-	Engineering	Modelling strategy for electromagnetic, mechanics and thermal
[136]	UK 2019	Life Cycle Modelling for MRO	Gas Turbine	Geometry Model	Boxer	Engineering	Simulation scaling and data-driven feedback
[155]	China 2020	Control performance monitoring	Coal-fired	Hybrid Model	MATLAB	Engineering/ Case Study	Off-design and dynamic operation
[140]	South Africa 2020	Predictive maintenance for cost-effective	Coal Fired	Empirical Thermo-hydraulic Model	PTB	Engineering/ Case Study	Accuracy -Model calibration within 5 % error
[156]	Germany 2021	Grate firing system modelling	Coal Fired	CFD	OpenFOAM	Engineering	Combustion behaviour for two different grate firing system
[134]	China 2020	Power System design optimization, fault analysis, and monitoring	General	Hybrid Model	-	Case Study	Consistency of virtual and real system during a real-time interaction
[142]	China 2019	Performance optimization during winter and summer	Coal Fired - Co-gen	Physic Model	Thermoflow	Case Study	Plant impacts under high frequency of load variation
[144]	Russia 2020	Evaluation of an access fuel flow by remote	Coal-fired	Regression Model	C#	Case Study	Plant monitoring and storage by remote

[130]	Tajikistan 2019	Improve the reliability of autonomous maintenance	RE Hydroelectric	Mathematical Model	-	Case Study	Actual turbine and generator modelling
[157]	Iran 2020	Wind turbine adaptive controllers	RE	DDPG	MATLAB	Case Study	Validation of dynamic behaviour of the pitch angle control
[143]	Poland 2019	Control strategies for transient operation	Coal Fired	Physic Model	Apros and Aspen Plus Dynamics	Case Study	Oxy combustion dynamic modelling and control strategies
[147]	France 2020	Digital twin modelling for nuclear reactor	Nuclear	Finite Element Model	Salome Meca	Case Study	FEM development as per visualization data
[150]	Malaysia 2020	Operator Training Simulator (OTS) system development	General	Physic Model	Visual Modeler	Training	Process control validation in dynamic operation