Transactions on Energy Systems and Engineering Applications

Review

Applications of Digital Twins in Power Systems: A Perspective

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Received: 1 September 2022; Accepted: 3 November 2022; Published: 4 November 2022

Abstract: Data science-based digital twin models of renewable energy system technologies developed in a real-time data-rich environment help develop better decisions and predictions than those in the present environment. Based on this real-time analysis of countrywide data, digital twin contributes to effective and reduced cost-based power system control at the localised level. Developing digital twin models from the collection of relevant data is an innovative technology. The challenge is how to leverage all the operational data and analyse the use of data from across transmission and distribution networks to help achieve the objectives. This paper presents an overview of the existing applications of digital twins in power systems.

1. Introduction

The energy system of the future is a work in progress to address the deregulation of electricity markets, and the deployment of wide and distributed energy resources [1]. At the same time, as announced by the United Nations Department of Economic and Social Affairs, affordable and clean energy has been announced as one of the 17 Sustainable Development Goals (SDGs) for an urgent call for action [2]. In addition, the New Zealand government has made a target for the electricity system to be completely renewable by the year 2050. How the power system eventually forms, such as the business models, the key players, and its architecture and how it works will be dependent on the impacts of the outcomes of trends, forces, regulations, and strategic actions by some of the diverse players in energy trading.

The digitalisation of the traditional generation plan and transmission has been proposed. The future power system will be so complex because of the multiple forces affecting various system levels, especially the Distribution Network Level. They are thousands of local distribution areas operated by distribution operators (suppliers) on top of the consumers, etc. Thus, it appears not too different, but the power flows

How to cite this article: Kamyabi, Leila; Lie, Tek Tjing; Madanian, Samaneh. Applications of Digital Twins in Power Systems: A Perspective. *Transactions on Energy Systems and Engineering Applications*, 3(2): 484, 2022. DOI:10.32397/tesea.vol3.n2.484

are no longer just one way from the bulk power system to the consumer end. In fact, the power flow will be extremely complicated to trace because it can be from one consumer to the other, consumer to the grid, grid to consumer, and some of them will be mobile/random due to the charging/discharging of electric vehicles. A major part of decision-making in the power industry has been the usage of highly technical power system models. The evolving research around digital twin models has also been a highly technical model that some of our industrial sectors use. However, a data science-based digital twin is a unique phenomenon, and a new trend in energy systems is starting to emerge right now.

These types of renewable energy resources, such as solar, photovoltaic (PV), and Wind Turbine Generation, depend on nature and its factors, including wind speed and direction, temperature, solar irradiation, and humidity. Therefore, the outputs are stochastic in nature. This necessitates using new data science-inspired real-time solutions to co-develop digital twins of large intermittent renewable plants alongside energy utilities, whose services could be delivered globally. Also, as indicated in [3], the natural and sometimes unpredictable factors that affect renewable energy sources make combining different types of renewable energy sources important. This increase the complexity of the energy efficiency of renewable energy.

In addition, in some other areas, such as offshore power systems, the new and driving concept of smart cities puts higher emphasis on having more on close monitoring and supervision of power systems at different levels of generation, storage and distribution. Data Science techniques to manage big data in real-time will ideally fit this stream. Online monitoring of the system's behaviour, performance, and status would also require addressing the system's efficiencies [1]. This requires an innovative system control that is not achievable solely based on traditional systems. Integrated Systems Modelling methods and concepts are needed to study self-organisation, complexity, emergent properties, and dynamical behaviour of complex systems for their holistic understanding, management, and development based primarily on Neural networks, Fuzzy and soft systems/Fuzzy Cognitive Maps, network modelling, and Mathematics. Other Advanced applications in computational early detection of mastitis and Computer-Based Decision Support Systems for complex systems are also needed. Due to the scale of the network and the amount of data that needs to be digitised, new techniques in data mining and AI approaches are needed to analyse and predict the behaviour of the complex system.

This paper presents an overview of the increased number of developments in applying digital twins to various parts of industries, especially in electrical power utilities.

2. Literature Review

Michael Grieves informally introduced the concept of digital twins (DT) in 2002 [4]. Since then, many definitions have been addressed, and through them, we can briefly define a digital twin as a digital replica of a physical system or an object, which is constantly evolving through connecting to the physical system [5, 6]. A well-designed digital twin creates real-time digital models which can diagnose the true value of heterogeneous data by integrating sensors, artificial intelligence, cloud computing, and machine learning [7]. DT applications can be divided into three main applications of conceptualization, comparison, and collaboration [8]. Since the emergence of DTs, they have been used in various industries, and their application can be divided into six primary areas [3] - see Figure 1:

- Manufacturing (consists of goods production activities).
- Services (general services activities, such as IT, energy systems, laboratories, etc.).
- Logistics (consist of activities which are related to logistics, such as material handling, routing, etc.).
- Healthcare (health operations activities, such as clinics, hospitals, etc.).
- Construction (civil construction related activities).

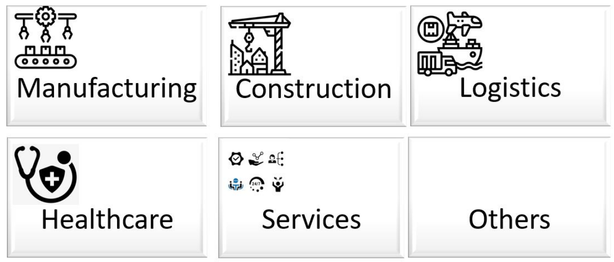

Figure 1. Digital Twin Primary Areas.

- Others.

In the power systems, based on the available models and methods, the digital twin technology can be integrated with the power system for different purposes, including optimisation design of the power grid, the simulation of power grid faults, virtual power plants, intelligent equipment monitoring, and other services [9]. However, in this paper, more specifically, the authors mostly imply the following aims of using digital twins [10]:

- Load balancing.
- Power management.
- Fault identification.
- Demand forecasting.
- Cyber security.
- Power monitoring system (PMS).
- Others.

In the following, some of the applications of digital twins in the power systems sections will be briefly explained.

2.1. Load balancing

In [11], a tree-shaped chained multi-hop digital twin algorithm (TUCM) is proposed to balance the network energy consumption and promote the network load. In this study, the nonuniform clustering method is applied to solve the problem. Since clustering methods play important roles in this kind of problem, applying other clustering methods may lead to better results. A dynamic load balancing method is proposed in [12]. In this study, the Hungarian algorithm is applied to solve the maximum matching of the bipartite graph, and to complete the match of the weighted bipartite graph Kuhn-Munkres algorithm is used. Because, in some cases Hungarian algorithm cannot find complete match results, using other algorithms leads to better results.

2.2. Power management

In [13], a multi-layer digital twin approach is introduced to reduce energy demands peak by shifting loads. In this study, an Internet of Things (IoT) smart gateway is used to collect hourly data on all appliances' consumption. But improving the time (for instance, collecting data every 30 minutes instead of 1 hour) will provide better results. Authors in [14] created the digital twin of a micro-grid to make an energy storage system optimal charging/discharging schedule. In the proposed framework, some supervised learning techniques such as MARS and decision trees are used to minimize electricity bills. To improve this research's results in the future, researchers can change predictors or each model's parameters. In [15], a new control system is proposed for renewable energy complexes that create digital twins of equipment. In this method, researchers used an algorithm to select a combination of renewable energy resources to increase energy efficiency.

2.3. Fault identification

Using renewable energy resources, especially offshore wind energy, is increasing. Therefore, some technical challenges related to frequency and voltage stability are rose. To reduce these challenges, authors in [16] proposed Direct Voltage Control (DVC). This method is tested for the three-phase line-to-ground fault, which is one of the most severe dynamic conditions in the network. Despite all the satisfactory results of the proposed method, this research has some gaps. For instance, it is not implemented for single-phase faults and is not expanded to large-scale offshore networks (equal to or greater than 2GW). A new DT-based method of fault diagnosis in photo voltaic (PV) systems such as building-integrated PV (BIPV) and rooftop is proposed in [17]. In this study, DT is developed to predict the measurable characteristic outputs of PV energy conversion unit (PVECU) through mathematical modelling. Unfortunately, it is not using a data-based approach. However, in [18], a new data-driven procedure is proposed to obtain the DT of a system. This method is based on the study of time series and the application of deep learning techniques to detect anomalies in the system. To remotely diagnose and investigate an ultrahigh-voltage converter station, authors in [19] proposed an IoT-based method named "Pavatar." This station converts direct current (DC) to alternating current (AC) of clean energy such as wind, and Pavatar predicts the system errors and diagnoses faults. Results show that in Pavatar, data sampling faces the problem of category imbalance. Therefore, using other learning techniques may lead to better results.

2.4. Demand forecasting

In [20], an ordinary differential equation, which is a novel class of deep neural network (DNN), is applied to solve the residential load demand forecasting problem. Despite an acceptable prediction accuracy level, this method suffers from high uncertainty in data attributes. Furthermore, this method is restricted to just analysing short-term load forecasting for residential household demands ranging from several minutes up to a few hours in the future. Solving this problem would be a promising idea for next studies. An energy management tool based on DT is proposed in [21]. This tool used machine learning modules to coordinate and control the interconnected energy assets in the system. In this paper, just local forecasting of the generations or demands is done. To fill this research gap, authors in [22] proposed a machine learning-based method to solve the integrated energy system scheduling problem with multiple uncertainties. In this study, a day-ahead scheduling method based on digital twins is used. Furthermore, a deep neural network method is proposed. This method is trained by learning from both historical forecasting errors and day-ahead forecasts to make a statistically day-ahead cost-saving schedule.

2.5. Cyber security

As information communication technologies (ICT) have been embedded in power systems, the risk of cyber security threats on power systems has grown substantially. These cyber-threats can attach to economic dispatch, power system state estimation, or power control systems, as indicated by [23]. To address this issue, in [24], an internet of things (IoT)- based digital twin of the cyber-physical system is proposed to ensure that the control system is operating properly. The DT does this by interacting with the control system and applying a control theory named Luenberger Observer (LO). This proposed DT is able to mitigate the coordinated false data injection and the denial of service (DoS) attacks. Although the results are acceptable, a fusion of a machine learning method such as deep learning and LO will improve the speed, accuracy, and predictability of attacks.

2.6. Power monitoring system (PMS)

In a wind turbine, because of gradual degradation, the gearbox being prone to failure. In [25], a digital twin method is proposed to monitor this component. In this paper, a vibration sensor is used to determine the occurrence of a fault. Similarly, in [26], a DT framework is suggested to predict the remaining useful life (RUL) of an offshore wind turbine power. The suggested framework has the potential to decrease the operational and maintenance cost of wind turbines. Additionally, the proposed DT framework could be used as a comprehensive platform for optimum predictive maintenance strategy with the potential of an accurate damage and RUL prediction for fixed and floating offshore wind turbines. In [27], a new approach is presented to monitor and operate all wind farms in parallel. This method integrates technical and business data into one single digital twin implemented via augmented reality (AR). In [28], a method based on creating a digital twin of a power transformer is proposed. This approach is used to manage the health of transformer equipment but, voltage, current and power monitoring in real-time are not considered. Hence, authors in [1] created the digital twin of the medium voltage (MV) sides of distribution transformers (T/F). In this study, measurements of the low voltage (LV) sides are used to monitor the waveforms of the MV sides. Therefore, voltage and current are monitored in real-time, and as a result, T/F power is calculated. However, the proposed digital twin fails to calculate the phase and magnitude of phase voltages of the MV side. Authors in [29] used digital twins to monitor the residual life of floating wind turbines' components, specifically the drivetrain main shaft. To do this, the authors applied the torsional dynamic model, but it seems that it is not applicable to other components, and researchers need to apply more detailed torsional models.

2.7. Others

In [30], the authors study the potential of digital twins in the power systems sector and discuss the importance and challenges of applying digital twins in power systems. DTs provide some benefits which motivate engineers to apply them to offshore wind turbines. Some of these pros are system behaviour prediction, rough environment simulations, less downtime, less maintenance cost, and improvement in the lifespan of systems, among others. All the mentioned benefits decrease expenses [31]. The accessibility of offshore wind turbines is challenging and needs to be approached in specific weather windows [32]. Furthermore, compared to the past, offshore wind turbine farm locations are further away from land, growing larger and more expensive. Therefore, decentralizing maintenance programs for offshore wind turbines is more critical than for the onshore wind turbines [33]. A new digital twin-based method for offshore structures is proposed in [34]. The digital twin is applied in this framework to update the structural reliability and quantify uncertainties. A probabilistic method using digital twin is presented in [35] to update the structural reliability of offshore wind turbine structures. By using digital twin information, the uncertainties related to the load modeling parameters in fatigue damage accumulation and structural dynamics can be quantified and updated. In [26], a new physics-based method is proposed to predict the remaining useful life (RUL) and damage accumulation of offshore wind turbine power converters. This method is successfully implemented on fixed and floating offshore wind turbine converters. However, the authors did not consider the boundary conditions related to the floating platform.

A new assessment procedure for distributed renewable energy resources (DRESs) impact at local and global levels is proposed in [36]. This method is based on using the power-hardware-in-the-loop (PHIL) technique, and the global level, via the integration of PHIL to the digital twin on the grid in real-time (RT) simulation. The DTs of the inverter model are built in [37] using the neural network (NN). NN-based identifier is used to replicate the dynamic behavior of the targeted control loop of the inverter.

To reduce the difference between the software-in-loop (SIL) and its actual controller, researchers in [38] used the concept of DT. In this study, SIL and hardware-in-loop (HIL) are integrated, and a new DT-based adaptive controller is introduced. Authors in [39] proposed a method to develop a medium voltage cable model to prevent failures caused by thermal stress in wind turbines. This model is created based on the combination of a real-time interpolation algorithm and a dynamic thermal model of an MV cable. A new method is proposed in [40] to develop a data-driven DT in the context of electrical energy generation. In this study, DT is used to provide the possibility of developing control algorithms that increase the efficiency, safety, and reliability of control objects. Authors in [41] provided a review paper about the frequent operational failures in wind turbines and their subsystems. This paper discusses technologies such as the internet of things and artificial intelligence that can be applied for monitoring wind turbines. In [42], a review of DTs application in smart energy grids is presented. Authors review the DT applications in the following domains: fault and security diagnosis, energy asset modeling, operational optimisation, and business models. Researchers in [43] developed a data-driven model to predict NOx emissions of power plants using informative operation data, which were selected by genetic algorithm. In [41], a hybrid modelling method based on operation data and first-principle mechanisms is proposed for the performance monitoring of control stage systems. In [44], authors proposed a new method based on digital twins to address the regularity difficulties problem in an electrical power system. Hence, this new management system supervises the substation more effectively. In [19], a digital twin framework is used for power flow monitoring by applying random matrix theory and deep learning.

3. Conclusion

The paper has presented a perspective on how the digital twin is becoming increasingly popular to be applied to overcome many complex problems in power systems. Today's power systems are very complex and dynamic due to the high penetration of renewable energy sources (RESs), Electric Vehicles, Energy Storage systems, Fast Charging Stations, etc. As a result, the amount of data and information is huge. Therefore, one needs to be aware that the technical risk we may face in delivering excellent research is the availability of a high-speed network. This can be managed by collaborating with the relevant party with access to an advanced network that allows high-speed network communications of data; otherwise, it is necessary to develop an alternative for doing it without a high-speed network platform.

Disclosure statement: The authors declare no conflict of interest.

References

[1] Panayiotis Moutis and Omid Alizadeh-Mousavi. Digital twin of distribution power transformer for real-time monitoring of medium voltage from low voltage measurements. *IEEE Transactions on Power Delivery*, 36(4):1952–1963, 2021.

[2] Independent Group of Scientists appointed by the Secretary-General. The Future is Now: Science for Achieving Sustainable Development (GSDR 2019). Technical report, United Nations, 2019. Available at https://sustainabledevelopment.un.org/content/documents/24797GSDR_report_2019.pdf.

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

[4] Anton Rassõlkin, Tamas Orosz, Galina Lvovna Demidova, Vladimir Kuts, Viktor Rjabtšikov, Toomas Vaimann, and Ants Kallaste. Implementation of digital twins for electrical energy conversion systems in selected case studies. *Proceedings of the Estonian Academy of Sciences*, 70(1):19 – 39, 2021.

[5] Barbara Rita Barricelli, Elena Casiraghi, and Daniela Fogli. A survey on digital twin: Definitions, characteristics, applications, and design implications. *IEEE Access*, 7:167653–167671, 2019.

[6] Aidan Fuller, Zhong Fan, Charles Day, and Chris Barlow. Digital twin: Enabling technologies, challenges and open research. *IEEE Access*, 8:108952–108971, 2020.

[7] Vivi Qiuchen Lu, Ajith Kumar Parlikad, Philip Woodall, Gishan Don Ranasinghe, and James Heaton. Developing a dynamic digital twin at a building level: Using cambridge campus as case study. In *International conference on smart infrastructure and construction 2019 (ICSIC) driving data-informed decision-making*, pages 67–75. ICE Publishing, 2019.

[8] Greyce N. Schroeder, Charles Steinmetz, Carlos E. Pereira, and Danubia B. Espindola. Digital twin data modeling with automationml and a communication methodology for data exchange. *IFAC-PapersOnLine*, 49(30):12–17, 2016. 4th IFAC Symposium on Telematics Applications TA 2016.

[9] Huaming Pan, Zhenlan Dou, Yanxing Cai, Wenzhu Li, Xing Lei, and Dong Han. Digital twin and its application in power system. In *2020 5th International Conference on Power and Renewable Energy (ICPRE)*, pages 21–26, 2020.

[10] Ali Aghazadeh Ardebili, Antonella Longo, and Antonio Ficarella. Digital twin (dt) in smart energy systems-systematic literature review of dt as a growing solution for energy internet of the things (eiot). *E3S Web of Conferences*, 312:09002, 2021.

[11] Wei Zhou. Research on wireless sensor network access control and load balancing in the industrial digital twin scenario. *Journal of Sensors*, 2022:3929958, 2022.

[12] Xueyong Tang, Yi Ding, Jinyong Lei, He Yang, and Yankan Song. Dynamic load balancing method based on optimal complete matching of weighted bipartite graph for simulation tasks in multi-energy system digital twin applications. *Energy Reports*, 8:1423–1431, 2022.

[13] Yasmin Fathy, Mona Jaber, and Zunaira Nadeem. Digital twin-driven decision making and planning for energy consumption. *Journal of Sensor and Actuator Networks*, 10(2), 2021.

[14] Hyang-A Park, Gilsung Byeon, Wanbin Son, Hyung-Chul Jo, Jongyul Kim, and Sungshin Kim. Digital twin for operation of microgrid: Optimal scheduling in virtual space of digital twin. *Energies*, 13(20):5504, 2020.

[15] A A Smirnov, V S Lunenko, and I A Boldyrev. Application of digital twins of equipment for managing complex renewable energy. *IOP Conference Series: Materials Science and Engineering*, 1035(1):012023, 2021.

[16] Saran Ganesh, Arcadio Perilla, Jose Rueda Torres, Peter Palensky, and Mart van der Meijden. Validation of emt digital twin models for dynamic voltage performance assessment of 66 kv offshore transmission network. *Applied Sciences*, 11(1), 2021.

[17] Palak Jain, Jason Poon, Jai Prakash Singh, Costas Spanos, Seth R. Sanders, and Sanjib Kumar Panda. A digital twin approach for fault diagnosis in distributed photovoltaic systems. *IEEE Transactions on Power Electronics*, 35(1):940–956, 2020.

[18] Kamel Arafet and Rafael Berlanga. Digital twins in solar farms: An approach through time series and deep learning. *Algorithms*, 14(5), 2021.

[19] Yuan He, Junchen Guo, and Xiaolong Zheng. From surveillance to digital twin: Challenges and recent advances of signal processing for industrial internet of things. *IEEE Signal Processing Magazine*, 35(5):120–129, 2018.

[20] Xiang Xie, Ajith Kumar Parlikad, and Ramprakash Srinivasan Puri. A neural ordinary differential equations based approach for demand forecasting within power grid digital twins. In *2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, pages 1–6, 2019.

[21] Edward O'Dwyer, Indranil Pan, Richard Charlesworth, Sarah Butler, and Nilay Shah. Integration of an energy management tool and digital twin for coordination and control of multi-vector smart energy systems. *Sustainable Cities and Society*, 62:102412, 2020.

[22] Minglei You, Qian Wang, Hongjian Sun, Iván Castro, and Jing Jiang. Digital twins based day-ahead integrated energy system scheduling under load and renewable energy uncertainties. *Applied Energy*, 305:117899, 2022.

[23] Yan Xu. A review of cyber security risks of power systems: from static to dynamic false data attacks. *Protection and Control of Modern Power Systems*, 5(1):1–12, 2020.

[24] Ahmed Saad, Samy Faddel, Tarek Youssef, and Osama A. Mohammed. On the implementation of iot-based digital twin for networked microgrids resiliency against cyber attacks. *IEEE Transactions on Smart Grid*, 11(6):5138–5150, 2020.

[25] Fei Tao, Meng Zhang, Yushan Liu, and A.Y.C. Nee. Digital twin driven prognostics and health management for complex equipment. *CIRP Annals*, 67(1):169–172, 2018.

[26] Krishnamoorthi Sivalingam, Marco Sepulveda, Mark Spring, and Peter Davies. A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective. In *2018 2nd International Conference on Green Energy and Applications (ICGEA)*, pages 197–204, 2018.

[27] Hergen Pargmann, Dörthe Euhausen, and Robin Faber. Intelligent big data processing for wind farm monitoring and analysis based on cloud-technologies and digital twins: A quantitative approach. In *2018 IEEE 3rd International Conference on Cloud Computing and Big Data Analysis (ICCCBDA)*, pages 233–237, 2018.

[28] Yong Yang, Zhu Chen, Jing Yan, Zhi Xiong, Jun Zhang, Hongxia Yuan, Yali Tu, and Tianyun Zhang. State evaluation of power transformer based on digital twin. In *2019 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI)*, pages 230–235. IEEE, 2019.

[29] Farid K. Moghadam and Amir R. Nejad. Online condition monitoring of floating wind turbines drivetrain by means of digital twin. *Mechanical Systems and Signal Processing*, 162:108087, 2022.

[30] Amir Ebrahimi. Challenges of developing a digital twin model of renewable energy generators. In *2019 IEEE 28th International Symposium on Industrial Electronics (ISIE)*, pages 1059–1066, 2019.

[31] ORACLE. Digital twins for iot applications a comprehensive approach to implementing iot digital twins. Technical report, ORACLE White Paper, 2017. Available at https://infotech.report/Resources/Whitepapers/a3323742-5fee-4df3-89fd-d9aeaa012ba6_digital-twins-for-iot-apps-wp-3491953.pdf.

[32] W. Yang. 18 - condition monitoring of offshore wind turbines. In Chong Ng and Li Ran, editors, *Offshore Wind Farms*, pages 543–572. Woodhead Publishing, 2016.

[33] Peter Tavner. *Offshore Wind Turbines: Reliability, availability and maintenance*. Energy Engineering. Institution of Engineering and Technology, 2012.

[34] *The True Digital Twin Concept for Fatigue Re-Assessment of Marine Structures*, volume Volume 1: Offshore Technology of *International Conference on Offshore Mechanics and Arctic Engineering*, 2018. V001T01A021.

[35] Dawid Augustyn, Martin D. Ulriksen, and John D. SÃ¸rensen. Reliability updating of offshore wind substructures by use of digital twin information. *Energies*, 14(18), 2021.

[36] Van Hoa Nguyen, Quoc Tuan Tran, Yvon Besanger, Marc Jung, and Tung Lam Nguyen. Digital twin integrated power-hardware-in-the-loop for the assessment of distributed renewable energy resources. *Electrical Engineering*, 104(2):377–388, 2022.

[37] Xinya Song, Teng Jiang, Steffen Schlegel, and Dirk Westermann. Parameter tuning for dynamic digital twins in inverter-dominated distribution grid. *IET Renewable Power Generation*, 14(5):811–821, 2020.

[38] Meisam Jahanshahi Zeitouni, Ahmad Parvaresh, Saber Abrazeh, Saeid-Reza Mohseni, Meysam Gheisarnejad, and Mohammad-Hassan Khooban. Digital twins-assisted design of next-generation advanced controllers for power systems and electronics: Wind turbine as a case study. *Inventions*, 5(2), 2020.

[39] O. Oñederra, F. J. Asensio, P. Eguia, E. Perea, A. Pujana, and L. Martinez. Mv cable modeling for application in the digital twin of a windfarm. In *2019 International Conference on Clean Electrical Power (ICCEP)*, pages 617–622, 2019.

[40] Makhsud Mansurovich Sultanov, Edik Koirunovich Arakelyan, Ilia Anatolevich Boldyrev, Valentina Sergeevna Lunenko, and Pavel Dmitrievich Menshikov. Digital twins application in control systems for distributed generation of heat and electric energy. *Archives of Thermodynamics*, 42(2), 2021.

[41] Gopi Krishna Durbhaka and Barani Selvaraj. Convergence of artificial intelligence and internet of things in predictive maintenance systems–a review. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, 12(11):205–214, 2021.

[42] Tudor Cioara, Ionut Anghel, Marcel Antal, Ioan Salomie, Claudia Daniela Antal, and Arcas Gabriel Ioan. An overview of digital twins application domains in smart energy grid. *ArXiv*, 2104.07904, 2021.

[43] You Lv, Carlos E. Romero, Tingting Yang, Fang Fang, and Jizhen Liu. Typical condition library construction for the development of data-driven models in power plants. *Applied Thermal Engineering*, 143:160–171, 2018.

[44] Chunsheng Hu, Wenbo Shi, and Lekai Jiang. Application case of digital twin technology in electric power system. *IOP Conference Series: Materials Science and Engineering*, 788(1):012083, 2020.