Energy Reports 8 (2022) 3704–3726

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Review article

Digital twin in energy industry: Proposed robust digital twin for power plant and other complex capital-intensive large engineering systems

Ahmad K. Sleiti [a,*], Jayanta S. Kapat [b], Ladislav Vesely [b]

[a] *Department of Mechanical & Industrial Engineering, College of Engineering, Qatar University, Doha, Qatar*
[b] *Department of Mechanical and Aerospace Engineering, CATER, University of Central Florida, Orlando, FL, USA*

ARTICLE INFO

Article history:
Received 27 November 2021
Received in revised form 7 February 2022
Accepted 28 February 2022
Available online 16 March 2022

Keywords:
Digital twin
Energy savings
Power plant
Dynamic system model (DSM)
Anomaly Detection and deep Learning (ADL)
Sensor network
Energy cyber–physical systems.

ABSTRACT

The complex future power plants require digital twin (DT) architecture to achieve high reliability, availability and maintainability at lower cost. The available research on DT for power plants is limited and lacks details on DT comprehensiveness and robustness. The main focus of the present study is to propose a comprehensive and robust DT architecture for power plants that can also be used for other similar complex capital-intensive large engineering systems. First, overviews are conducted for DT key research and development for power plants and related energy savings applications to provide current status, guidelines and research gaps. Then, the requirements and rules for the power plant DT are established and the major DT components are determined. These components include the physics-based formulations; the statistical analysis of data from the sensor network; the real-time data; the pre-performed localized in-depth simulations to predict activities of the corresponding physical twin; and the system Genome with a digital thread that connects all these components together. Recommendations and future directions are made for the power plant DT development including the need for real data and physical description of the overall system focusing on each component individually and on the overall connections. Data-driven algorithms with capabilities to predict the system's dynamic behavior still need to be developed. The data-driven approach alone is not sufficient and a low-order physics based model should operate in tandem with the updated latest system parameters to allow interpretation and enhancing the results from the data-driven process. Discrepancies between the dynamic system models (DSM) and anomaly detection and deep learning (ADL) require in-depth localized off-line simulations. Furthermore, this paper demonstrates the advantages of the developed ADL algorithm approach and DSM prediction of the DT using vector autoregressive model for anomaly detection in utility gas turbines with data from an operational power plant.

Contents

* Corresponding author.
E-mail address: asleiti@qu.edu.qa (A.K. Sleiti).

https://doi.org/10.1016/j.egyr.2022.02.305

Nomenclature

ADL	Anomaly detection and Deep Learning
AMO	Advanced Manufacturing Office
AI	Artificial Intelligence
BIM	Building Information Model
CI	Computational Intelligence
CFD	Computational Fluid Dynamics
CHP	Combined Heat and Power
CS	Cyber Security
CPS	Cyber–Physical System
DDM	Digital Dynamic Mirror
DNN	Dynamic Nature of the Networks
DSM	Dynamic System Model
DSN	Distributed Sensor Network
DT	Digital Twin
DTAS	Digital Twin Artifacts System
ECPS	Energy Cyber–Physical Systems
EECM	Equipment Energy Consumption Management
EIA	U.S. Energy Information Administration
EOS	Equations of State
FEM	Finite Element
GAM	Generalized Additive Model
GHG	Global Greenhouse Gas
GPA	Gas Path Analysis
GT	Gas Turbine
HMIs	Health Management Information system
HRSG	Heat Recovery Steam Generator
IDEAS	Institute for the Design of Advanced Energy Systems
IDS	Integrated dynamic simulation
IGV	Inlet Guide Vanes
IMT	Intelligent Machine Tool
IoT	Internet of Things
IR	Industrial Robot
LDS	localized, in-depth simulation
MCR	Maximum Continuous Rating
MECS	Mobile Edge Computing System
ML	Machine Learning
NZEB	Net Zero Energy Buildings
O&M	Operation and Maintenance
PCA	Principal Component Analysis
PE	Physical entity
PHM	Prognostics and Health Management
PP	Power Plant
PPDT	Power Plant Digital Twin.
PSE	Process Systems Engineering (PSE)
PV	Photovoltaic
RAM	Reliability, Availability and Maintainability
SMT	Surface Mount Technology
ST	Steam Turbine
VAR	Multiple-stage vector autoregressive model
VC	Virtual Commissioning
VE	Virtual equipment
VR	Virtual Reality
WEEE	Waste from disassembling Electronic and Electric Equipment

1. Introduction

The global energy consumption is projected by EIA to increase by 50% between now and 2050 (EIA, 2022). On the flip side, the non-renewable energy production technologies contribute to global greenhouse gas (GHG) emissions by more than 70%, Center for Climate and Energy Solutions (C2ES). This presses the global power industry to aggressively look for more efficient ways of operations to reduce the negative impacts of variability of fuel costs, weather changes, power plant cycling, unplanned outages, etc. The existing solutions to such problems are of incremental nature and new technologies and approaches are inevitable to transform the energy production sector and to meaningfully improve the energy efficiency in industrial, buildings, service and transportation sectors. One of these technologies is the use of digital twin (DT) for power plants to facilitate rapid transformation of power systems and to improve flexible operation. The key challenges facing the energy industry, methods to improve flexible operations and the benefits of implementing DTs are summarized in Fig. 1 (based on Zitney (2019)). These challenges can be mitigated by improving the flexible power plant operation via digitalization and connected plant technologies, which can be achieved using power plant DT. As shown by Fig. 1, the digital transformation of power plants is accelerating, and DTs are key enabling technologies for R&D with future applications in cyber–physical systems for reducing design time and cost.

Digital twin is defined by the CIRP Encyclopedia of Production Engineering (Stark and Damerau, 2019) as a digital representation of a machine, device, service, object, asset or product–service system that tracks the characteristics, properties, conditions, and behaviors of the system by means of models, information, and data". Other comprehensive definitions of DT can be found in Negri et al. (2017) and characterization of the DT, key terminology and associated processes are summarized in Jones et al. (2020). While the implantation of DT in the energy industry is currently limited (as

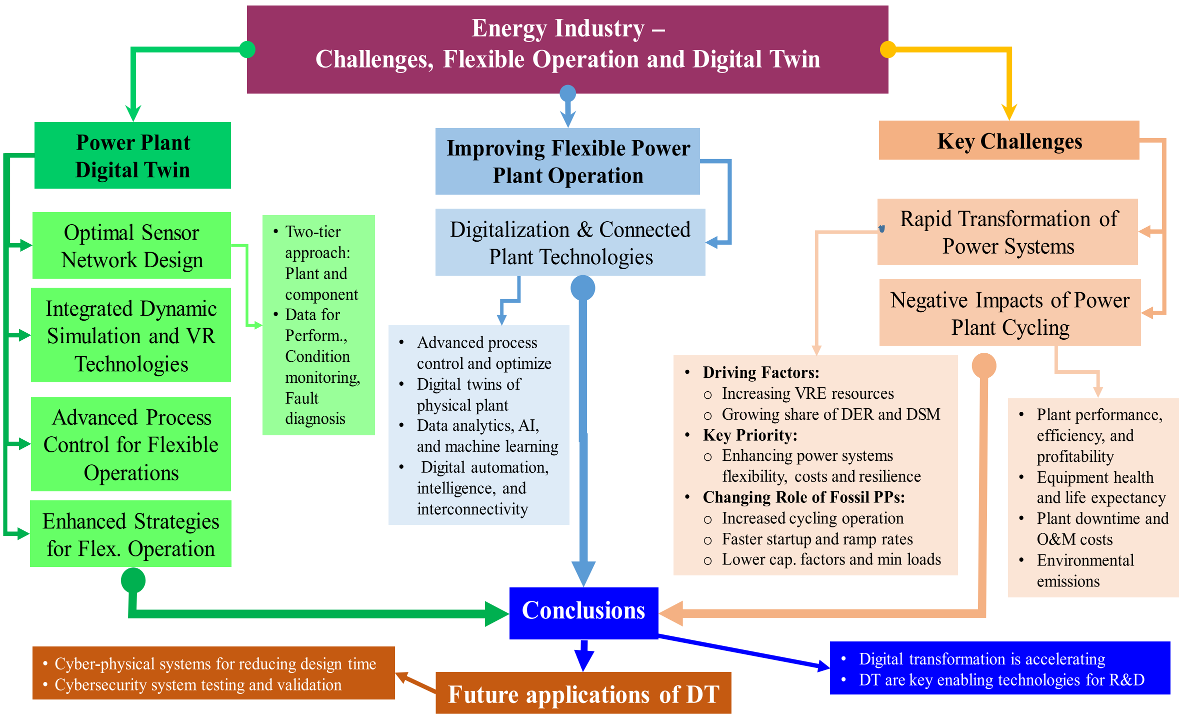


Fig. 1. Challenges facing the energy industry, improving power plant flexible operation, and digital twin.

will be shown in subsequent sections), DT is being implemented in various industries for the last 2 decades (Negri et al., 2019b; Tao et al., 2019). Examples of these various industries that are in the implementation stage of DT include: manufacturing (Jones et al., 2020; Al-Ali et al., 2020), concepts, technologies, and industrial applications (Liu et al., 2020); demonstrating the potential of real time data acquisition in production systems (Uhlemann et al., 2017a), synchronized production operation system (Zhang et al., 2020), applications in manufacturing (Cimino et al., 2019); smart cities and healthcare (Fuller et al., 2020; Augustine, 2020); construction (Lu et al., 2020b), automotive (Tharma et al., 2018), agriculture, cargo shipping and drilling platform (Mayani et al., 2018); automobile, aerospace, and smart manufacturing (Lu et al., 2020a); electricity (Qi et al., 2019); 3D printing (Mukherjee and DebRoy, 2019); machine tools (Armendia et al., 2004); NASA, U.S. Air Force vehicles (Glaessgen and Stargel); model-based system engineering (Madni et al., 2019) and several others. Digital twins have several kinds of industrial applications (Liu et al., 2020) including real-time monitoring, production control, performance prediction, human–robot interaction, optimization, asset management and production planning. In service, applications of DT include predictive maintenance, fault detection & diagnosis, state monitoring, performance prediction, and virtual test (Liu et al., 2020), diagnosis and adaptive degradation analysis of rotating machines (Wang et al., 2019b), prognostics and health management (PHM) (Tao et al., 2018).

Digital Twin for power plants can be defined as combined physics based and analytical methods used to model the individual components of the power plant and the system. These models can be applied to new and existing power plants to provide design limits of the power production units under different operation conditions such as changes in weather data, ambient temperature, humidity, variable load, fuel mix, etc. In combination with advanced prediction, control and optimization techniques, the outcome of these DT models can improve the power plants performance, reliability, availability, maintainability and flexible operation. By utilizing data from sensors' network, the models are able to enhance the efficiency for different operational scenarios considering all kind of tradeoffs. Further, DTs can be integrated with decision making algorithms to allow making changes in real time. For power plants, DT applications include: performance and cost optimization; asset management; control with advanced edge computing; cyber defense; and processing "big data" using clouds and specialized platforms. An ideal digital twin for power plants and other capital-intensive large engineering systems must be both comprehensive, as described above, and robust in terms of its capability to age as the physical twin does using physics based foundation that is augmented by empirical data such as operational, outage, part-load condition, and site specific environmental data; ability to perform dynamic estimations and model tuning using data from available sensors, ability to handle fouling in the pipelines, heat exchangers, rotor blades; blockage of film cooling holes; operation problems such as inlet guide vanes (IGV) flutter and failure, malfunctioning of thermocouples, pressure, flow and power measuring devices, etc. To the best of the authors' knowledge, such comprehensive and robust DT for power plants does not exist yet and the main goal of the present work is to propose one. The current state of DT research in the energy sector and the main contributions of the present work are provided in the next subsections.

1.1. Current state of digital twin research in the energy sector and for power plants

In the energy production sector, because of renewable integration, future power plants will become more complex with Power-to-X, Electrolysis to green hydrogen, onsite storage of hydrogen, and use of pure or blended hydrogen, etc. Such power plants will require DT architecture to achieve high Reliability, Availability and Maintainability (RAM) at lower cost. Another energy-related application of DT is for energy savings in the industrial, service, buildings, and transportation sectors. The importance of industrial energy savings is asserted by many initiatives worldwide (Teng et al., 2021) including the establishment

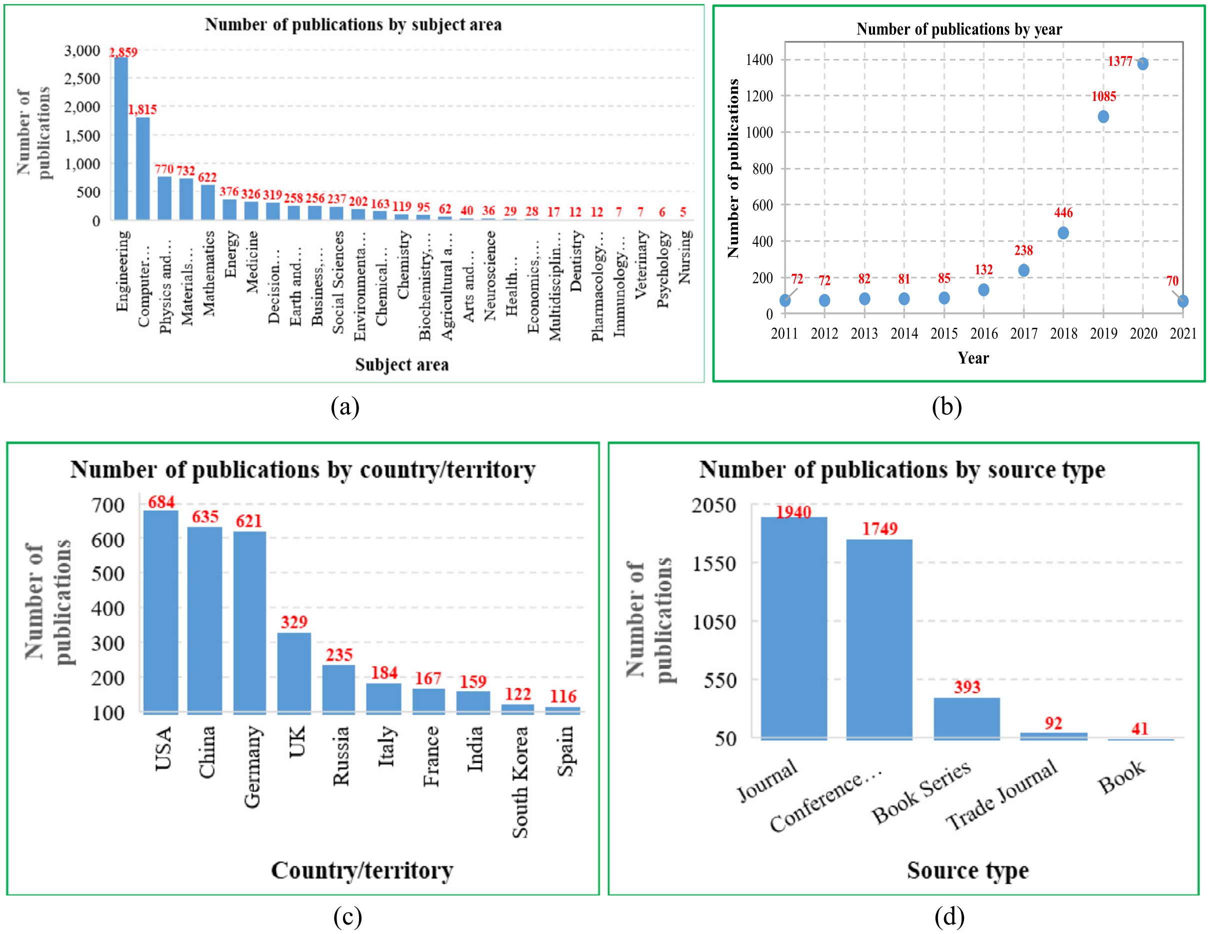


Fig. 2. Number of all DT publications by subject area, year, country/territory and source type (from Scopus).

of Advanced Manufacturing Office (AMO) of the US Department of Energy to improve the energy efficiency across the industrial sectors (US Department of Energ, 2020). Other countries and regions have adopted energy efficiency initiatives including the European Union (European Commission, 2020; EED, 2012), China (IEA, 2018), India (Bureau of Energy Efficiency (BEE) M. of P.G. of I, 2018), South-East Asia (Ministry of Energy Green Technology and Water, 2015), the Middle East and North Africa (Open Knowledge Repository, 2020), etc. However, as mentioned above, applications of DT in the energy production industry and for energy savings are limited in open literature. To demonstrate this limitation, a search of the keyword "digital twin" on Scopus revealed a total of 4695 documents on several research fields as shown by Fig. 2, of which only 376 documents are related to energy, Fig. 2a. This Figure also shows the subject areas, where DT is being implemented including engineering, medicine, social sciences and others. The publication rate has been in the rise as evidenced by Fig. 2b with USA, China and the European Union in the lead, Fig. 2c. Most of these publications are published in journals, conference proceedings and book series, Fig. 2d.

DT publications related to energy, in general, are provided in Fig. 3. Out of all 376 publications, the majority of 226 publications are on the area of engineering, Fig. 3a, while the rest are on earth sciences, mathematics, computer science and environment. This implies that DT research related to energy is still in its infantry stage and all subject areas can still benefit from its advantages. Furthermore, the low number of DT publications on the energy field by year, Fig. 3b, by country, Fig. 3c by source type, Fig. 3d, confirms the necessity of research in this untapped area. It is worth mentioning that Scopus as a source for DT related publications is used here as an indicator of the limited research publications on DT for energy applications. However other sources of publications were consulted and provided in the rest of the article including IEEE, ASME, GE, Siemens, etc.

Digital twin research publications for power plants in particular are very limited. Only three articles were found on DT for fossil fuel power plants: Zitney (2019), Xu et al. (2019) and Yu et al. (2020); two articles for DT in nuclear power plants: Patterson et al. (2016) and Okita et al. (2019); and five articles on DT for renewable energy systems: Ebrahimi (2019), Kahlen et al. (2016), Sivalingam et al. (2018), Moussa et al. (2018) and Jain et al. (2020). There are several other articles on DT at the component level of power plants. However, all these articles, as will be detailed in Sections 2 and 3 below, did not include enough details on the comprehensiveness/robustness of their DTs or details on the used physics based models, artificial intelligence and enabling technologies capabilities.

1.2. Manuscript contributions and organization

While digital twin research and architectures for many industries have been developed or in advanced development stages, digital twins for power plants are numbered in open literature and the available DTs are lacking or missing details on how comprehensive and robust is the DT and details on its capabilities. The main focus of the present study is to propose comprehensive and robust DT architecture for power plants that can also be used for other similar complex capital-intensive large engineering systems. The novelty, necessity and advantages of such DT will be assessed by reviewing the available power plant DT research

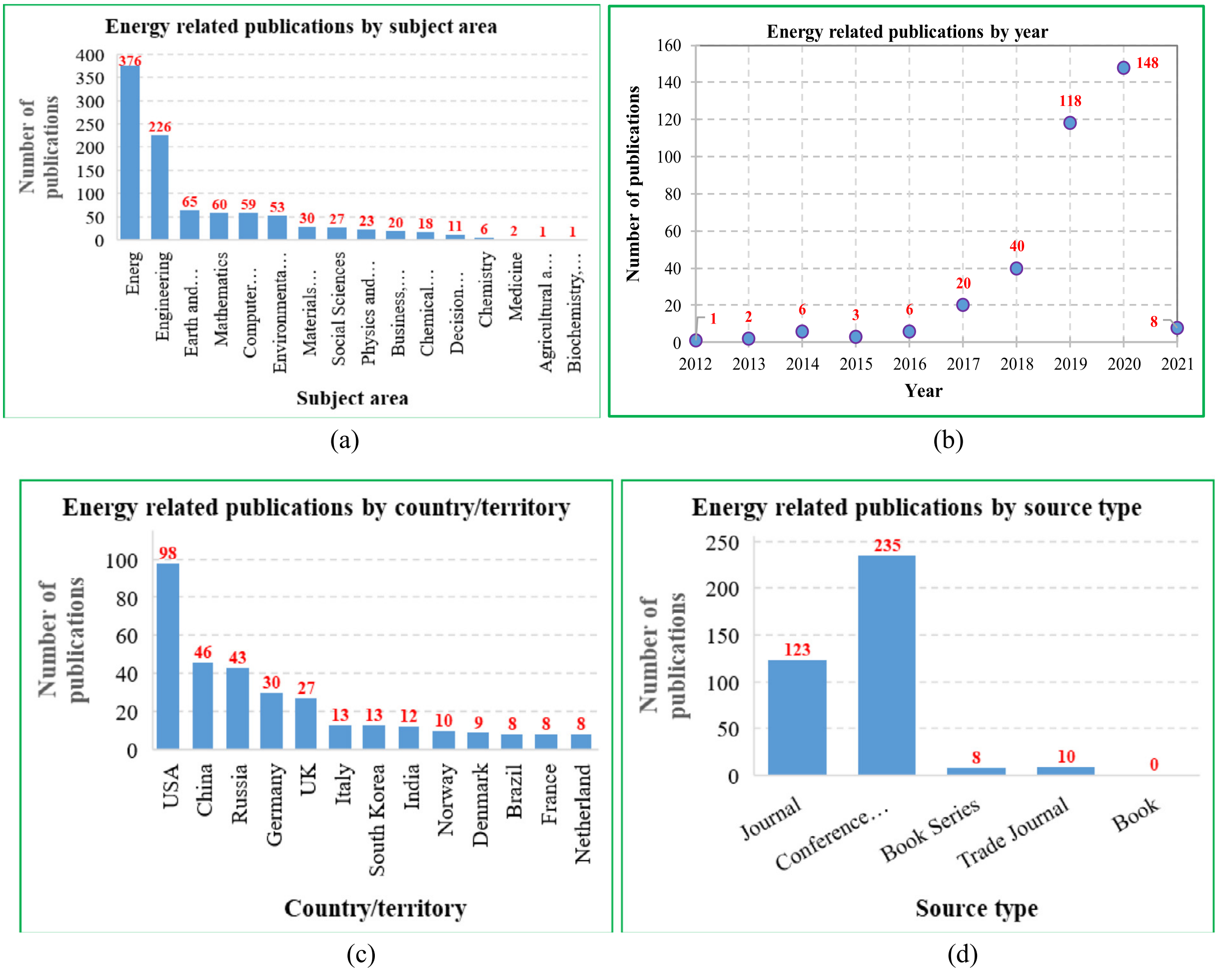


Fig. 3. Energy related digital twin publications by subject area, year, country/territory and source type (from Scopus).

and energy efficiency DT research that potentially can benefit the development of power plant DT. More specifically, the main contributions of the present work include:

i. Overview of DT key research related to power plants and energy savings applications that could benefit the development of power plant DT (PPDT). This overview is intended on highlighting the available so far power plant DT applications, frameworks and architectures and to highlight important findings and research gaps.
ii. Proposing new comprehensive and robust DT architecture for power plants. For this, the requirements for PPDT will be established and the major DT components will be determined including the physics-based formulations; the statistical analysis of data from the sensor network; the real-time data; the pre-performed localized in-depth simulations to predict activities of the corresponding physical twin and the system Genome with a digital thread that connects all these components together.
iii. Demonstrating the advantages of the developed ADL algorithm approach and DSM prediction of the DT using vector autoregressive model for anomaly detection in utility gas turbines with data from an operational power plant.

The rest of the manuscript is organized as follows: Section 2 details the DT applications that are mostly related to power plants and their components. Section 3 overviews DT applications for energy savings that benefits the development of PPDT. The proposed DT for power plants and other similar complex systems is provided in Section 4 and future work and conclusions related to PPDT are summarized in Section 5.

2. Overview of DT research for power plants

Development efforts of DT technology in the energy industry are ongoing and gaining more momentum at fast pace. So far, these efforts have been documented only in limited number of publications. The aim of this section is to provide a comprehensive and timely review of the PPDT and to provide a framework for implementing DT in energy production systems. The energy production key applications of DT are summarized in Table 1 categorized by their application type. These applications include electricity generation and power distribution; renewable and nuclear power; vehicles, energy storage, batteries; and scheduling of energy projects. As the focus of the present work is on PPDT, further discussions are provided in this section on DT applications for conventional, nuclear, and renewable energy power plants; smart energy systems; and energy cyber–physical systems.

2.1. Digital twin for fossil fuel power plants and their components

The energy industry is actively pursuing the tremendous opportunists of DT applications for power plants. The key challenges facing the energy industry, the need for improving flexible power plant operation and implementing power plant DT were introduced by Fig. 1 of the introduction section. For rapid transformation of power systems and to reduce the impact of plant

Table 1
Overview of DT in energy production industry.

Application type	Ref.	Description
Electrical power industry, including electricity generation, electric power distribution	Zitney (2019)	DT for flexible power plant operation
	Sládek and Maryška (2018)	Business potential of emerging technologies in decentralized energy industry
	Klein et al. (2020)	Pressure-driven dynamic simulation to provide a detailed, transient simulation model, a digital twin, of an air separation unit
	Saad et al. (2020a)	DT for energy cyber–physical systems based on IoT and cloud computing
	Scheibe et al. (2019)	Analysis study in a power system simulation tool
	Pileggi et al. (2019)	Detect and analyze anomalies in a flexible energy deployment
	Brosinsky et al. (2020)	Digital Dynamic Mirror (DDM) for grid control
	Park et al. (2020a)	Optimization model for microgrid energy storage operation/scheduling
	Saad et al. (2020b)	DT for Networked Microgrids Resiliency against Cyber Attacks
	Kozhevnikov and Kaplin (2019)	Fault diagnosis and maintenance of power grid equip. and transmission lines
	Barszcz and Zabaryłło (2019)	A method for automated fault detection with analytical rotordynamic model
	Errandonea et al. (2020)	Review of DT for maintenance
	Peng and Wang (2019)	Condition monitoring for power converters
Renewable energy industry	Oñederra et al. (2019)	Predictive maintenance for windfarm
	Andryushkevich et al. (2019)	Power supply system with renewable energy sources
Nuclear power industry	Lin et al. (2021)	Semi-autonomous management and control system for advanced reactors to prevent peak fuel temperature from exceeding safe levels
Internet of Vehicles, energy storage, batteries	Zhang et al. (2019)	Electric vehicles, analyzing the collected data of energy use, charging and waiting time
	Merkle (2019)	Implement DT framework in a cloud-computing environment to estimate the SOC of battery modules
	Li et al. (2020)	Cloud management for battery with online estimation of charge and health
	Park et al. (2021)	Solid oxides electrolyte materials for lithium batteries
Sustainable project scheduling	Chakrabortty et al. (2019)	Applied to a real-life energy system

Table 2
Fossil fuel power plant DT models in open literature.

Description	DT model	Calibration	Validation	Findings
DT for coal-fired thermal power plant to analyze operation, optimization and economics. Xu et al. (2019)	ThermoflowTM with boiler, steam-turbine islands and emission control equipment models. O&M design specification data at 320-MWe base load.	Using real operating data from the distributed control system	Simulating the performances of various part-load-operating cases	Irregular load changes, thermal stresses, shortened lifespan and increasing O&M costs. CHP cogeneration improves efficiency.
Hybrid modeling and DT development method of control stage systems. Yu et al. (2020)	3 parts: flow rate calc. of high pressure control valves using operation data, flow and efficiency derivation.	330 MW steam turbines and 1000 MW ultra supercritical steam turbine.	5-day operation data for hybrid modeling and 5-day operation data to develop DTs.	Suitable for online performance monitoring and for integrating more renewables with higher efficiency and safety.

cycling, the power plant flexible operations can be improved via digitalization and connected plant technologies using DTs. However several DT key components need further research and development. The sensor network design is one of these components that can be optimized using two-tier approach: plant and component and using field data for performance improvement, condition monitoring and fault diagnosis. Integrated dynamic simulation (IDS) and virtual reality (VR) technologies, advanced process control and strategies for flexible operation of the power plant are the other key components of DT that need further development.

Only handful DT concepts for power plants and their components were found in open literature. For example, Zitney (2019) presented dynamic model-based DT, optimization, and control technologies for improving flexible power plant operations. For future work, the authors emphasized the application of DT in cyber–physical systems for reducing design time and operational risks and in cybersecurity system testing and validation. Another two studies by Xu et al. (2019), Yu et al. (2020) as shown in Fig. 4a and b, respectively, and summarized in Table 2, where directly related to thermal power plants. In Xu et al. (2019) a case study of DT modeling analysis is introduced on power-plant-performance optimizations on a 320-MWe coal-fired thermal power-plant unit. Their digital concept uses ThermoflowTM software that has imbedded models for the emission control equipment, the steam turbine island and the boiler island. The results showed reduction in coal consumption of 3.5 g/kWh that worth large fuel-cost savings annually. For the electricity-generation only mode (in summer), the thermal efficiency dropped 6% following the grid demand of load changes from 100% maximum continuous rating (MCR) down to 30%MCR. For the combined heat and power (CHP) cogeneration mode (in winter) and for the same boiler load, the plant's operating profit increased with increasing district heating duty. However, the work in Xu et al. (2019) was oriented toward the results of using DT and description of how optimization can improve the operation and reduce cost. No details were provided on the models used for their DT or on the optimization techniques and algorithms.

In Yu et al. (2020), a hybrid modeling method was proposed based on collected operational data for performance monitoring of control stage system of thermal power plants. Their modeling method uses flow rate calculation of high pressure control valves and flow and efficiency calculations of control stages. They validated the method using two case studies of a 330 MW subcritical steam turbine and a 1000 MW ultra-supercritical steam turbine, for which they developed DTs of control stages. Results show average relative errors within 1% between calculated and measured values of exit pressure and temperature, suggesting that plant-wide DT development and online performance monitoring are possible. Although the studies by Zitney (2019), Xu et al. (2019) and Yu et al. (2020) are good demonstration examples of using

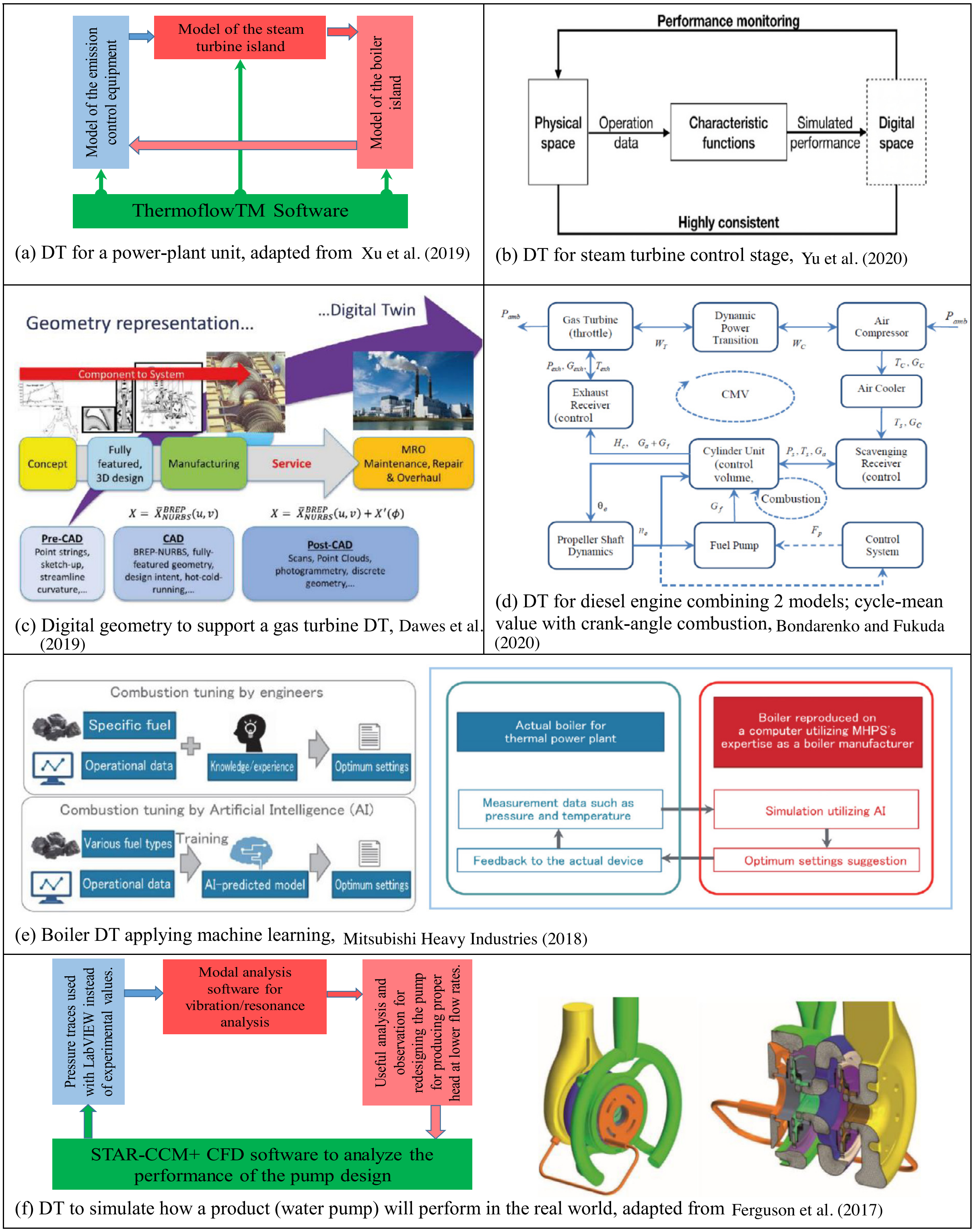
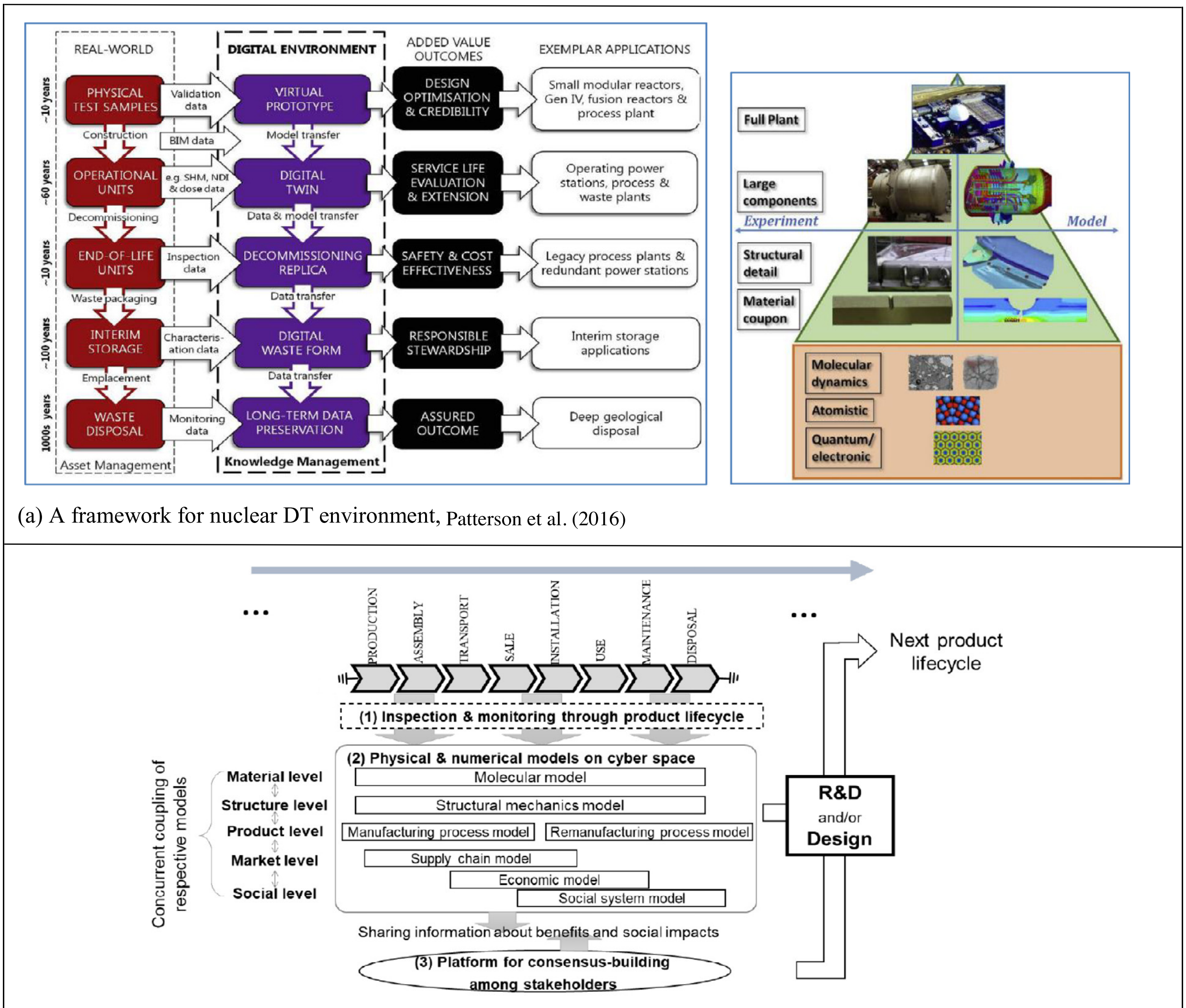


Fig. 4. DT concepts for power plants and their components.

DT for power plants, they still lack a holistic approach to full digitalization. The DT developed in Yu et al. (2020) was only at the control stage level that can be useful for developing DTs for other components but still does not address all requirements for power plant DT as a system.

The other DT concepts in Fig. 4c to 4f are also at the component level of power plants. Dawes et al. (2019) discussed digital geometry, as opposed to classical CAD approach, to support a gas turbine DT, Fig. 4c. The authors suggested that the DT should be an integrated, based on physics simulation (aero-thermal-mechanical, manufacturing, erosion & corrosion, wear & degradation, cost & life economics). Three key challenges were identified: scale of simulation; scaling the simulation; and responding to data driven feedback.

A diesel engine's DT for predicting propulsion system dynamics was developed by Bondarenko and Fukuda (2020), Fig. 4d.



(a) A framework for nuclear DT environment, Patterson et al. (2016)

(b) DT artifact system (DTAS) applied to a range of artifacts, from nuclear power plants to home appliances, Okita et al. (2019).

Fig. 5. Digital twin concepts for nuclear power plants.

Their modeling approach combines continuous time domain cycle-mean value engine model with the crank-angle resolved phenomenological combustion model, satisfying the real-time execution constraint. They used the integral form of the energy and mass conservation equations with Wiebe combustion model to come up with a set of nonlinear algebraic equations resulting in faster solutions and better accuracy than traditional approaches.

Mitsubishi Hitachi Power Systems (MHPS) (Mitsubishi Heavy Industries, 2018), Fig. 4e, developed DT for coal-fired boilers. The DT collects the measurement data of pressure, temperature and flow rate; utilizes AI technology including machine learning and MHPS's expertise; and reproduces a virtual boiler that provides optimum settings feedback to the control system of the real boiler. Taiwan Power Linkou Power Plant Unit 2 (800MW) showed 100 million yen annual cost reduction. The ultimate goal of the development of this DT technology is to establish automatic autonomous operation in the future.

Water pumps are used in power plants extensively, however specific applications of DT for water pumps in power plants were not found in literature. A study of water pump DT that can be extended to power plant applications can be found in Ferguson et al. (2017), Fig. 4f, who implemented the DT concept to tackle design challenges in water pumps using a simulation package from Siemens PLM Software. They used an example focuses on a large flood control axial pump for the city of New Orleans, designed to provide durable performance under severe weather conditions. The complex geometry of the pump was imported into STAR-CCM+ and discretized using the automated polyhedral and prism layer meshing capability. In combination with LabView pressure tracks and vibration software, they reached optimum design of the pump for the intended operation.

2.2. Digital twin for nuclear power plants

Applications of DT in nuclear power plants can be found in Patterson et al. (2016), Okita et al. (2019) as shown in Fig. 5. Patterson et al. (2016), Fig. 8a, proposed framework for a DT composed of prototype design of nuclear plants, operations, decommissioning, storage and waste disposal. The DT has series of interconnected multi-scale, multi-physics models with real data from prototypes, in-service monitoring and inspections, post-shut-down inspections, and in-situ monitoring of stored waste. The gaps, implementation and advantages of the proposed DT are identified and discussed emphasizing the dependence on future advances in high performance computing and on developing algorithms for processing huge data and on the importance of obtaining data via measurement innovations, analysis and uncertainty.

Okita et al. (2019) proposed a general DT of artifacts (DTAS) concept, which can be applied to large artifact systems such as nuclear power plants and small artifacts such as home appliances. The structure of DTAS consists of inspection technique that can detect the current state of structural materials, see Fig. 5b, to evaluate their degradation and integrity. DTAS components include physical and numerical models in cyber space such as manufacturing/remanufacturing, supply chain, economic and social models. The social system models, however, are challenging because they are related to value creation in societies, which is not easy to describe mathematically.

2.3. DT for renewable energy generators

DT concept can play major role for optimal design and reliable functioning of large renewable energy systems, however, according to (Ebrahimi, 2019), no serious strategy and comprehensive study have been yet proposed. Ebrahimi (2019) discussed the necessity and challenges of DT models of large renewable energy generators and introduced a comprehensive modeling strategy for developing a multi-domain live simulation platform for wind and hydro power plants, Fig. 6a. Large scale energy systems such as wind farms are complex systems and as such the DT concept was used by Kahlen et al. (2016), Fig. 6b, to change system design, manufacturing and operation. This resulted in reducing the unpredicted undesirable (UU) behavior of these complex systems and augmenting Systems Engineering. Sivalingam et al. (2018) reviewed and proposed methodology to predict the useful life for offshore wind turbine power converter in DT framework, Fig. 6c, for predictive maintenance. For hydro generators, Moussa et al. (2018), Fig. 6d, presented an existing large hydro generator based on partial DT concept and models using finite element method. A synchronous machine case study is considered, where both sets of simulation and experimental results are used to validate the model by performing no-load and sustained short circuit tests according to IEEE 115 standard. This DT concept still under development and needs to be completed to be able to perform condition monitoring, diagnosis and prognostics functionalities. DT approach for fault diagnosis in distributed photovoltaic systems, Oñederra et al. (2019), is shown by Fig. 6e, and will also be discussed in Section 3 below as the case serves as an example for both energy savings in buildings and for PV renewable energy applications of DT.

In addition to the above applications, Brosinsky et al. (2018) introduced a dynamic digital mirror concept of a DT centric control for power systems. A DT interface for managing a wind farm was patented by Lund (2018) with a graphical user interface (GUI) displaying a digital equivalent of the wind farm and a control icon. The digital equivalent of the wind farm includes environmental information and a digital representation of each of the wind farm turbines.

2.4. Energy management and control DT for smart energy systems

Energy management tool that can be used across different energy sectors is presented in O'Dwyer et al. (2020), Fig. 7a, with optimal control, scheduling, forecasting and coordination services of energy assets for a district. The idea is for a single open-source optimization framework to be applied across multiple energy vectors, providing local government the opportunity to coordinate different assets. Case studies were conducted for integrated low-carbon heating for social housing and electric vehicle charge management in Greenwich, London. The paper illustrates the theoretical methodology, the software architecture and the DT environment, however considerations for aging of the subsystems and the overall systems are not taken.

2.5. DT for energy cyber–physical systems

Modeling method of energy cyber–physical systems (ECPS) for several applications including in energy industry was introduced by Saad et al. (2020a), Fig. 7b. DT types to cover high- and low-bandwidth applications are tested and validated using Amazon Web Services (AWS) as cloud host. The experimental results confirmed the feasibility of DT for the ECPS based on cloud computing and IoT technologies with 3.7% normalized mean-square error for the low-bandwidth DT case and the accuracy of the proposed high-bandwidth DT, reached 98.2% in terms of voltage estimates.

Talkhestani et al. (2019) proposed DT and intelligent DT architectures for cyber–physical production systems. For implementation and evaluation, they used a method for heterogeneous data acquisition and data integration and an agent-based method for DTs simulations. Their proposed intelligent DTs is partly realized for a metal forming use case, however its realization for energy cyber–physical system was not carried out, which is a subject for future research.

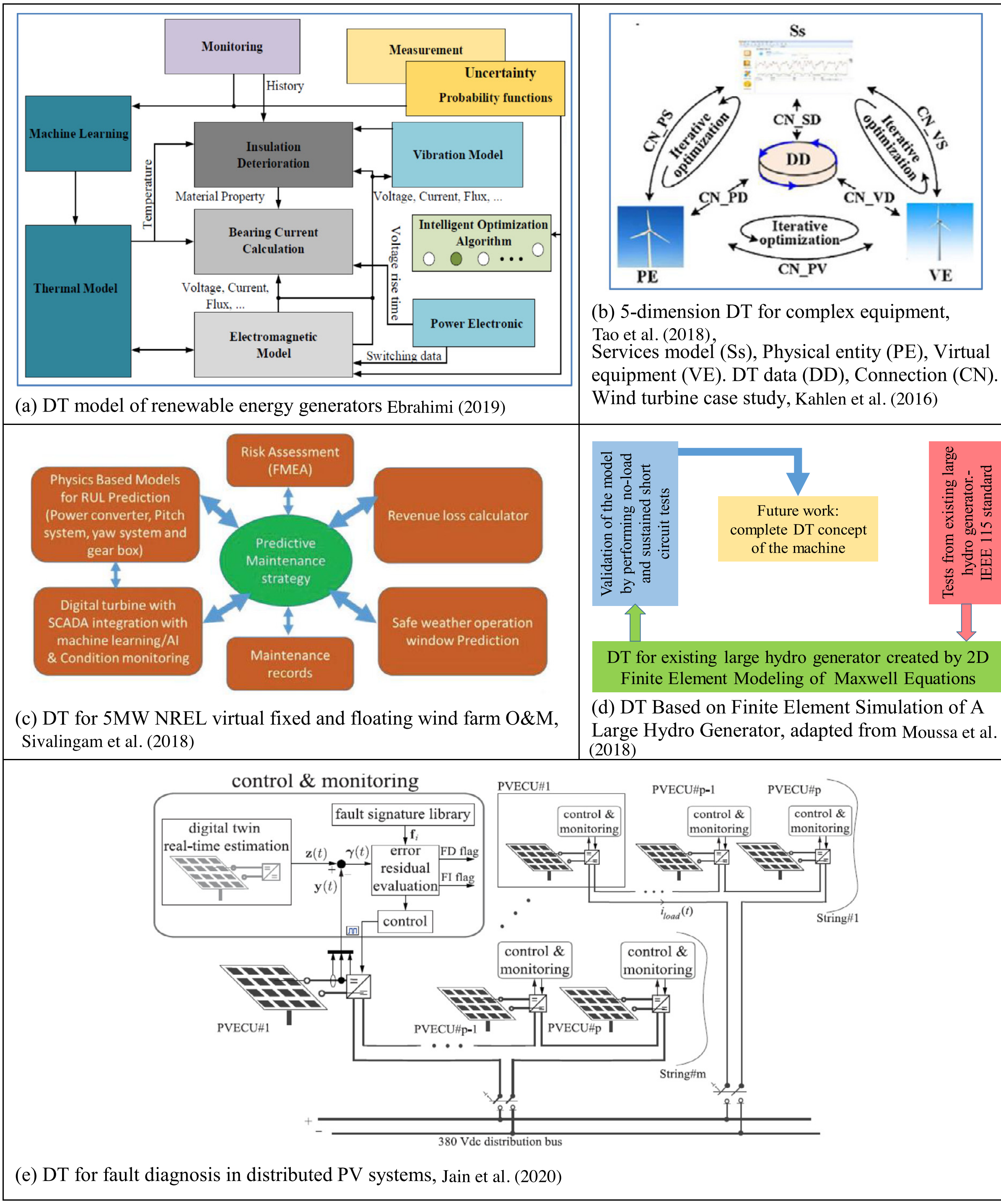
To conclude this section, the main observation is that the available DT research for power plants is very limited with only three articles were found on DT for fossil fuel power plants: Zitney (2019), Xu et al. (2019) and Yu et al. (2020); two articles for DT in nuclear power plants: Patterson et al. (2016) and Okita et al. (2019); and five articles on DT for renewable energy systems: Ebrahimi (2019), Kahlen et al. (2016), Sivalingam et al. (2018), Moussa et al. (2018) and Jain et al. (2020). There are several other articles on DT at the component level of power plants. However, all these articles did not include details on the comprehensiveness/robustness of their DTs or details on the used physics based models, artificial intelligence and enabling technologies capabilities.

The main challenges and research gaps facing DT R&D for power plants include:

- Optimization of sensor network design needs
- Developing and implementing integrated dynamic simulations and virtual reality (VR) technologies.
- Advancing process controls and enhancing strategies for flexible operations,
- Realization of DT for energy cyber–physical systems, and for energy management and control for smart energy systems.
- A holistic approach is needed for developing and implementing DT for power plants to account for renewable integration, energy storage choices, autonomous operation, full and part load conditions, aging of the DT, transient operation and other factors.

3. Overview of DT for energy savings applications

Key energy savings applications of DT that can serve the development of DT for power plants are summarized in Table 3 categorized by their application type with brief description of the main features. The examples in Table 3 include energy savings applications in production engineering, monitoring, manufacturing, buildings and pumping and ventilation systems. Further discussions of DT for these energy savings applications are provided next.



(a) DT model of renewable energy generators Ebrahimi (2019)

(b) 5-dimension DT for complex equipment, Tao et al. (2018), Services model (Ss), Physical entity (PE), Virtual equipment (VE). DT data (DD), Connection (CN). Wind turbine case study, Kahlen et al. (2016)

(c) DT for 5MW NREL virtual fixed and floating wind farm O&M, Sivalingam et al. (2018)

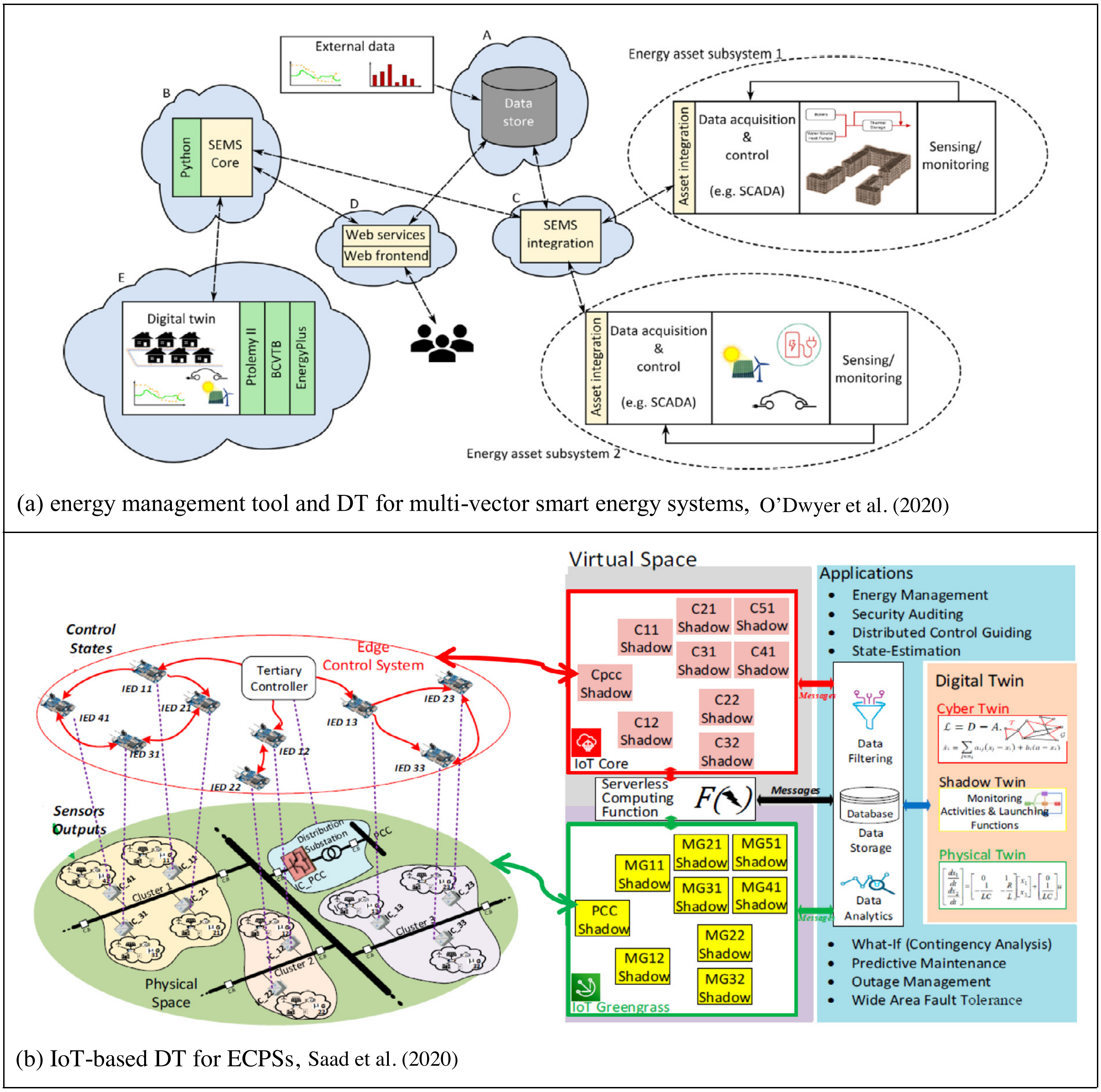
(d) DT Based on Finite Element Simulation of A Large Hydro Generator, adapted from Moussa et al. (2018)

(e) DT for fault diagnosis in distributed PV systems, Jain et al. (2020)

Fig. 6. Digital twin concepts for renewable energy systems.

3.1. *DT for energy savings in manufacturing*

In a recent review by Teng et al. (2021) on DTs for industrial energy savings applications, the potential for a more accurate and effective DT-based infrastructure was discussed. The authors proposed to standardize and modularize industrial data infrastructure for smart energy savings and provided a guideline for implementing advanced energy-saving systems. A DT for smart manufacturing to reduce energy consumption for a robotic cellular was proposed by Vatankhah Barenji et al. (2020). The approach implements real time optimization of motion planning in robotic cellular of the physical and virtual layer, Fig. 8a, based on which the DT driven facility is designed. Several observations and findings were reported for IoT implications with the new DT environment. Machining data application and service based on intelligent machine tool (IMT) DT were presented in Tong et al. (2020). Multi-sensor fusion technology is adapted for real-time data acquisition and processing. MTConnect protocol and components were used for transmission and storage of data. Multiple forms of health management information system (HMIs) and applications are developed for analysis in DT, including machining trajectory, status and energy consumption. The authors used the IMT DT model for analysis of machine tool dynamics, contour error estimation and compensation. For energy monitoring



(a) energy management tool and DT for multi-vector smart energy systems, O'Dwyer et al. (2020)

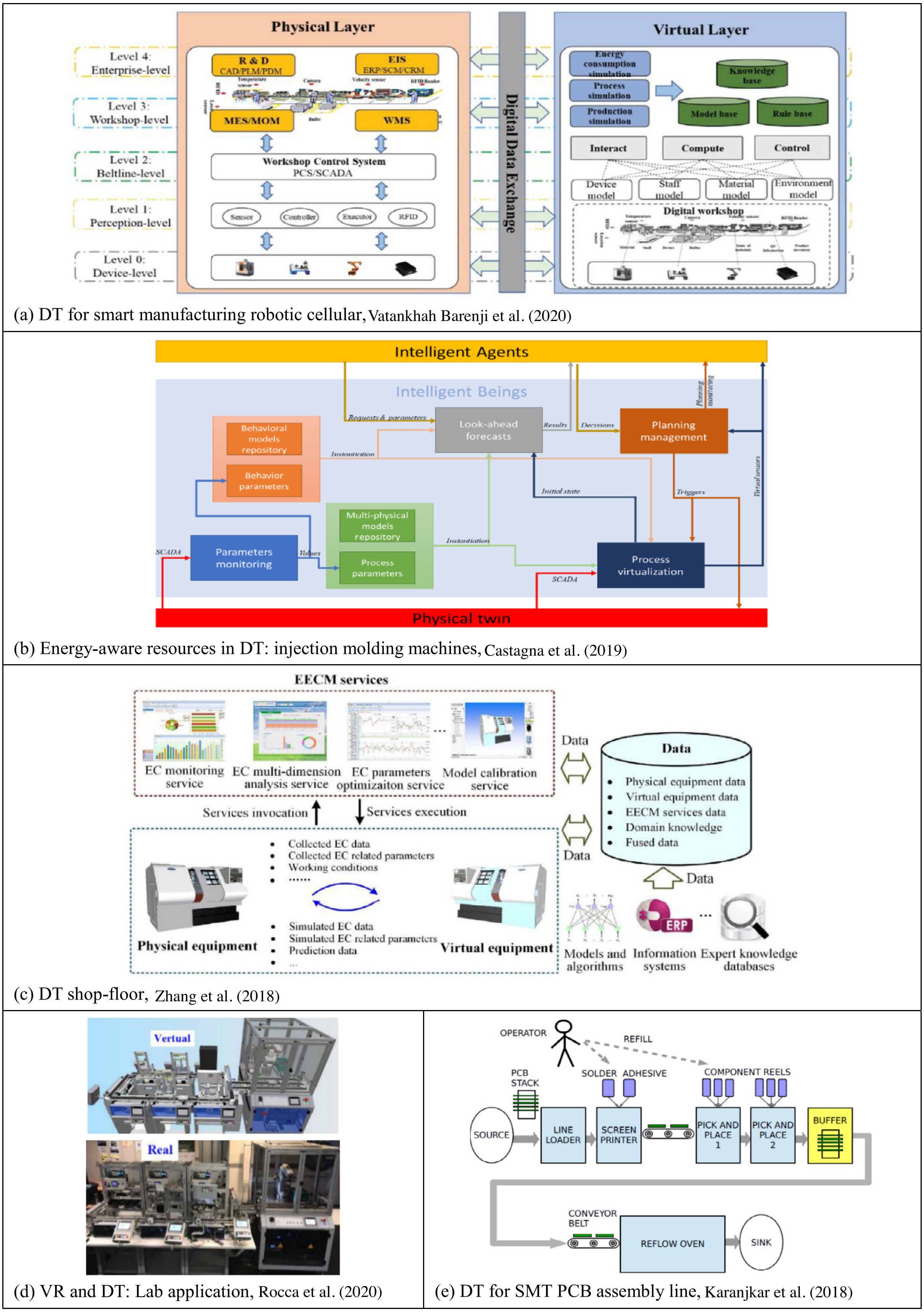
(b) IoT-based DT for ECPSs, Saad et al. (2020)

Fig. 7. Concepts of DT for energy management and control for smart energy systems and for energy cyber–physical systems (ECPSs).

and management of injection molding machines, Castagna et al. (2019) introduced a framework integrating the models inside the twin of the ARTI architecture and proposed a methodology to implement the DT on a resource, see Fig. 8b. Zhang et al. (2018b) used DT shop-floor (DTS) in the equipment energy consumption management (EECM) to improve the energy efficiency, Fig. 8c. In Rocca et al. (2020) DT concept was used for energy savings optimization of the waste from a process of disassembling electronic and electric equipment (WEEE) using automated simulation tools and manufacturing line, Fig. 8d. Energy optimization case study was presented in Karanjkar et al. (2019) using IoT-based DT in automated surface mount technology (SMT) assembly line with legacy machines, Fig. 8e. Sensors were used to measure energy consumption and other machine activities and open source tools for the DT. A buffering-based solution was suggested based on the gathered data to improve energy efficiency. The DT implementation showed energy consumption reduction of 2.7 times with minor effects on line throughput.

3.2. DT for minimizing energy consumption in mobile edge computing

A mobile edge computing system (MECS) with communications and delay tolerant services was considered in Dong et al. (2019) to minimize the energy consumption per bit (the only study found in open literature on this field). This is done by optimizing resource allocation, user association, and offloading probabilities constrained by requirements of service quality. They proposed a deep learning (DL) architecture, where a DT of the real network is used to train the DL algorithm off line, Fig. 9. To account for the dynamic nature of the networks (DNN), the DT sorts out the variation of real networks and updates the DNN. An optimization algorithm is proposed for resource allocation and offloading probabilities that achieved energy savings with less computational resources. The MECSs are energy-intense consuming systems with potential for significant energy savings, which calls for more research using DT approach.



(a) DT for smart manufacturing robotic cellular, Vatankhah Barenji et al. (2020)

(b) Energy-aware resources in DT: injection molding machines, Castagna et al. (2019)

(c) DT shop-floor, Zhang et al. (2018)

(d) VR and DT: Lab application, Rocca et al. (2020)

(e) DT for SMT PCB assembly line, Karanjkar et al. (2018)

Fig. 8. DT concepts for energy savings in manufacturing.

Table 3
Overview of DT for energy savings applications.

Application type	Ref.	Description
Production engineering	Hauf et al. (2017)	Automated production; energy efficiency with virtual commissioning (VC)
	Negri et al. (2019a)	Monitor the functional behavior of the production system and evaluating its energy consumption
	Howard et al. (2020)	DT for Commercial Greenhouse Production
	Howard et al. (2021)	For green house growers for developing energy flexibility solutions with constraints for processes and products
	Gupta and Basu (2019)	Aluminum smelting and emerging technology like Industry 4.0, toward reduction of energy and making Al production sustainable.
Monitoring appliances, machines, tools, compressors	Bayer et al. (2018)	Aircraft high lift system
	Kychkin et al. (2019)	Monitoring and control cyber–physical system (CPS) of compressors
	Sun et al. (2019)	Energy consumption of cutting tools
	Song et al. (2019)	Performance prediction of electro-optical detection system using Modulation
	Yue et al. (2019)	(dynamic Bayesian network)
Manufacturing	Liu et al. (2019)	Energy consumption for remanufacturing shop-floor
	Xiang et al. (2019)	green manufacturing, energy consumption management
	Oyekan et al. (2019)	Industrial robots and humans, metrics and kinetic energy for human reactions
	Anton et al. (2020)	DT on a distributed cloud in a shop floor with SCARA assembly robots
	Kannan and Arunachalam (2019)	For Grinding Wheel, increases energy and resource efficiency. Development of intelligent grinding wheel.
	Pombo et al. (2020)	
	Wang et al. (2019a)	Energy efficient manufacturing in synchronous and asynchronous systems using event driven online machine
	Park et al. (2020b)	Smart manufacturing operations DT for service functionality
	Cardin et al. (2020)	For injection molding machines
	Gaikwad et al. (2020)	For additive manufacturing
Data centers, building industry	Brannvall et al. (2019)	Cooling of IT equipment, tuning of server fan controllers
	Mateev (2020)	Business cases and best practices in design of IoT solutions for buildings
Pumping systems	Carrillo Peña et al. (2019)	Visualizing pumps in series or in parallel to adjust operating conditions to achieve higher efficiency in response to changes in conditions downstream
Ventilation system	Kychkin and Nikolaev (2020)	Mine ventilation control system architecture

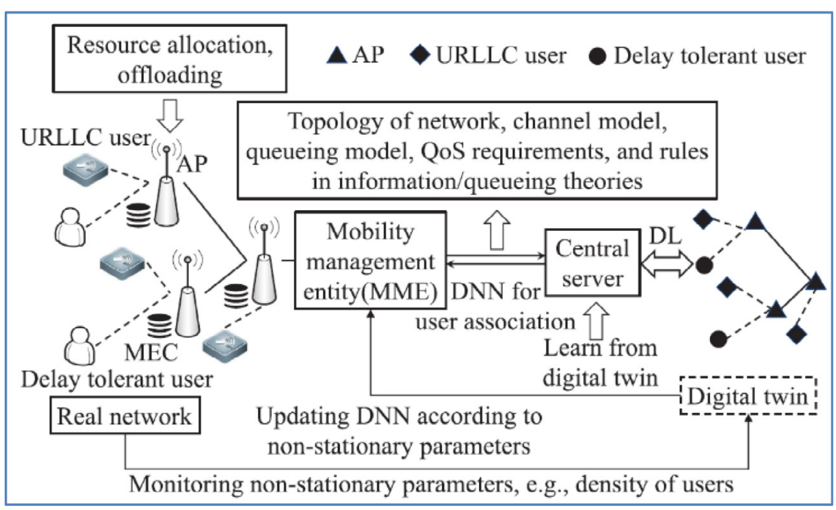


Fig. 9. DT to minimize energy consumption for mobile edge computing system, Dong et al. (2019).

3.3. Robot DT for energy savings

Autonomous robotized facilities with maintenance capabilities in the energy industry was discussed in Pairet et al. (2019). A video was presented of ORCA Hub simulator, a framework for three autonomous systems (Husky, ANYmal and UAVs) on an offshore platform DT for training and testing human–robot collaboration; inspection and emergency response. In Yan et al. (2018) energy saving of industrial robots (IRs) is investigated for environment protection and cost reduction. In their paper, energy modeling method of IRs based on DT is proposed, which includes physics based energy model of the physical IRs, 3D virtual robot model, DT data, and ontology based model to map the virtual to the physical model. Results of case study validation show that the DT modeling method predicted the IRs energy consumption efficiently.

3.4. DT for energy savings in buildings

Only 3 studies were found in open literature that used DT for energy savings in buildings; (Lydon et al., 2019; Jain et al., 2020; Kaewunruen et al., 2018). A building simulation of a heating and cooling system integrated with a lightweight roof structure was presented in Lydon et al. (2019). The concrete roof structure is shape optimized to provide a low-energy building element, which supplies space conditioning from geothermal source. The approach uses building physics analysis for initial system performance and a parametric geometry model to apply the pipework to a roof shape. Then, a less-resolution method is used to add the characteristics of the system to a whole building simulation model to develop control strategies. The research found that the digital fabrication approach helped identifying the needed alternations to the building design process.

Rooftop and building-integrated distributed photovoltaic (PV) DT design methodology was presented by Jain et al. (2020) including mathematical analysis, simulation study, and experimental validation for fault diagnosis. The DT estimates the measurable characteristic outputs of a PV unit in real time and the fault is detected by comparing the error in the measured and estimated outputs. Using a PV prototype, the experimental results show detection and identification of ten different faults. The time to fault detection in the power converter and the electrical sensors showed higher fault sensitivity than existing approaches.

The case study of existing buildings in Kaewunruen et al. (2018) investigated technical and financial viability of Net Zero Energy Buildings (NZEB). Evaluations to improve the NZEB are performed using a flow chart with a Building Information Model (BIM). This BIM or DT is then used to visualize the available options to estimate costs and production issues of NZEB. The authors concluded that the DT is feasible for renewable technologies applied on the NZEB buildings highlighting a case study in the UK with a payback period of 23 years.

To conclude this section, the challenges and research gaps facing DT R&D for energy savings applications that can serve the development of PPDT include:

- While the above DTs for energy savings demonstrated advantages in their intended applications, important DT aspects were not fully considered such as aging of the DT, detecting anomalies in real-time and answering what–if scenarios for transient operation. These aspects will be addressed in Section 4 below for the proposed in this study DT.
- Handling the data, processing infrastructure, and incomplete data acquisition systems in existing facilities, Máša et al. (2018), Weyer et al. (2015), Uhlemann et al. (2017).
- Standardization and modularization the systems' data infrastructure and development of efficient robust approach for analysis of data driven processes and data acquisition, (Weyer et al., 2015).
- The complexity arising from energy usage of hundreds of processes, Zhang et al. (2018a), which was addressed in Shrouf et al. (2017) by using multi-level energy data processing at the process, machine, production lines and production levels.
- Potential for blockchain technology, Teng et al. (2021), Andoni et al. (2019), Lu et al. (2019).
- Exploration and implementation of DT for new applications such as pipe networks for oil, gas and CO_2 transportation (Sleiti et al., 2020c) and many others.

In summary, these examples and approaches of using DT for energy savings in manufacturing, mobile edge computing, robots, and buildings can serve as guidelines for similar and extended processes and applications for power plant DT. Based on the findings from the review of DT for energy production and power plants (Section 2), DT for energy savings (Section 3) and the identified research gaps, a robust DT for power plants is proposed in Section 4 below. This DT is designed to also be used for other similar complex capital-intensive large engineering systems.

4. Proposed robust DT for a power plant and other similar complex capital-intensive large engineering systems

In this section, efforts are proposed that will lead to an algorithm or software platform consisting of several specialized, open-domain and/or commercial software to create a "Digital Twin" (DT) of a power plant, and other similar complex capital-intensive large engineering systems. Such a DT can be used for condition-based maintenance, prediction of life-remaining, autonomous operation of a power plant or similar systems. Because of renewable integration, future power plants will become more complex with Power-to-X, Electrolysis to green hydrogen, onsite storage of hydrogen, and use of pure or blended hydrogen, etc. Such power plants will require DT architecture, such as the proposed here, to achieve high RAM at a lower cost. Condition based maintenance and autonomous plant operation will become more important in the coming decades. As various forms of short term versus long term energy storage technologies are introduced, and as various forms of fuels will be used either in blended or pure form with implications on both emissions and life of components, on-the-fly decision for operation and maintenance will become too complex. For example, whether to deplete battery storage or to use stored green hydrogen, whether to use higher fraction of hydrogen or lower fraction in blended fuel, whether to reduce the load to a part load condition or to use on-site electrolyzer to produce and store hydrogen for later use are some of the decisions that plant operators of the future have to take. The proposed DT platform is intended to address such issues. In addition, the DT platform can also be used to assess the remaining life for various parts, and hence for planning a service interruption or prediction of a component's fault according to real-time measurement and historical data.

4.1. Requirements for DT architecture

The DT architecture is based on an integrated algorithm that combines, on a real-time basis, a dynamic system model utilizing a physics-based low-order model of the system, and statistical and machine learning algorithms applied to data from the various sensors employed. In order to design a DT architecture, it is necessary to define several requirements, which have to be considered in the DT architecture:

- The DT must have the up-to-date physical dimensions and model (System Genome or SGenome) of the physical twin — The DT must "age" as the physical twin does.
- The DT must accept and process continuous data stream from a multitude of sensors (referred to as distributed sensor network (DSN) – just as a human brain does.
- Must include a low-order, physics-based, dynamic system model (DSM) that can run in real-time. This is essentially the Cyber–Physical model or System of the Physical Twin.
- Must be able to detect, in real-time, anomalies based on data received from DSN, to apply machine learning or deep learning principles to identify the serious anomalies. This feature is referred to as anomaly detection and deep learning (ADL).
- Must be able to refer to a look-up table of previously performed localized, in-depth simulation (LDS) solutions to explain differences between ADL and DSM, and update System Genome.
- Must be able to trigger alarms and warnings in real-time that would lead to maintenance schedules, and/or suggest off-line, new LDS in case of unexplained disagreements.
- Must be able to answer what–if scenarios for transient operation or changes.

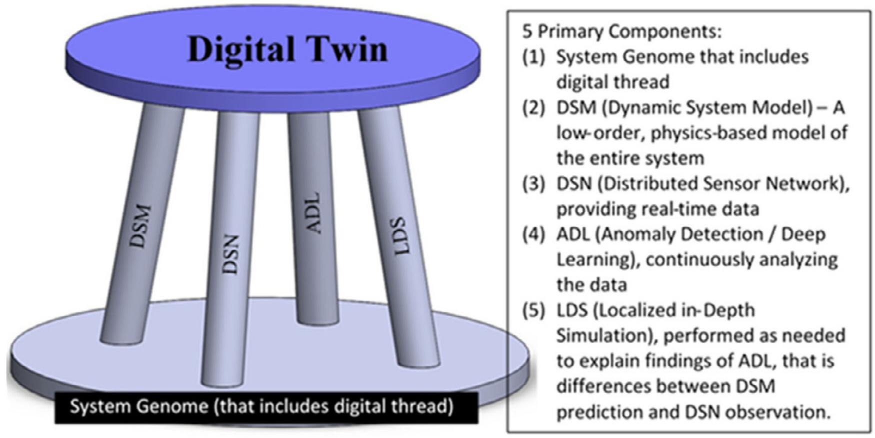


Fig. 10. Components of Digital Twin architecture, based on Goyal et al. (2019).

According to the above rules and requirements, the proposed DT architecture consists of five key components, see Fig. 10. These DT components are: DSM or physics-based formulations of a system of interest (power plant, air craft, storage, etc.), ADL or statistical analysis of data from the sensor network, as well as DNS or real-time data of a system of interest, and LDS or pre-performed localized in-depth simulations to predict activities of the corresponding physical twin. All these four components are connected to the system Genome with a digital thread.

4.2. Overall flowchart of the proposed power plant DT architecture

The overall DT architecture is shown in Fig. 11, where number (1) is a dynamic system model (DSM), which is physics-based, low-order model of the power plant and number (2) is a data-based model that would incorporate the latest techniques in machine/deep learning and artificial intelligence (ADL). The DT architecture compares the results from DSM and ADL. In the case of "unacceptable" levels of disagreement, and if the difference between DSM and ADL can be traced back to sensor failure(s), the sensor database (DNS), i.e. number (3) and the digital thread of the system, i.e. number (4) are updated. Here (3) is a distributed, massive sensor network that should be flexible enough to incorporate newer sensors and automatically discard unnecessary and failed sensors, and (4) is digital thread or plant model that must be updated on real-time in order to accommodate "aging" and localized failures. Otherwise, "unacceptable" levels of disagreement will force the DT algorithm to look-up a collection of pre-performed localized in-depth simulations (LDS) of various components of the system, i.e. number (5), which is an off-line or non-real-time tool for detailed, localized simulation of flow, structures, acoustics, vibrations, combustion etc. If the differences can be explained due to, say, aging or wear and tear of the components, the digital thread is updated so that the DSM will utilize the updated digital description subsequently. Otherwise, alarms are raised and additional off-line LDS may be performed until the differences can be explained.

The DT shown in Fig. 11 is a complex architecture with several issues that need special handling. For example, currently many of the data-based algorithms have shown tremendous promise but the accuracy of these algorithms is far from satisfactory, which is very important for ADL. The problem is basically in the quality of datasets (negligible repeatability or security and liability issues) (Loboda, 2016; Zhao et al., 2016). However, according to published literature, the gas path analysis (GPA) has been used consistently in the industry to predict the deviation from the expected performance of gas turbines or small subsystems (Volponi, 2014; Volponi and Tang, 2016).

4.3. Components of the power plant DT architecture

Referring to Fig. 11, the detailed description of each circled component(s) is as follows:

(1) Physics-based dynamic system model (DSM)

The DSM is oriented toward the development of the mathematical model of the problem/system. This mathematical model is written for real-time solutions with dynamic effects as well as steady-state behavior. The mathematical model can be written in one source programing language or can use commercial software. The IDAES (Institute for the Design of Advanced Energy Systems) is one of the open source software and can be used for this purpose (Gunter et al., 2018). IDEAS is a new advanced Process Systems Engineering (PSE) with capabilities to design and optimize current and future potential power systems with dynamic simulation. IDEAS is written in Python, which is an open-source, fast, and user-friendly programing language. IDAES uses several Python software packages. The main open-source dependency is Pyomo, which IDAES uses for optimization. Pyomo is the Python software package collection for the definition and formulation of the optimization models. DT based optimization methods can be used such as the one proposed by Guerra et al. (2019) that minimizes the maximum absolute position error based on fine tune method. Also, multi-objective optimization for economy, environment and society sustainability (Rivas et al., 2020) can be incorporated in the optimization processes.

The IDAES architecture is designed as the main flowsheet, which is divided into the unit's models, which include thermodynamic properties models and support submodules, see Fig. 12. All input parameters, and boundary conditions are defined in the main code (flowsheet). The flowsheet also defines the connection between components and whether the system is open or closed.

The unit models (pump, compressor, boiler, heat exchanger, etc.) are the main models for the calculation of individual components. The unit model defines constraints and equations for each component with the geometry and material properties. The support submodules are modules, which define the control volume of the model, reaction, phase, or connection between unit models. The support submodules are the main mathematical codes for a defined overall system, for example, for direct-fired supercritical CO_2 power cycle (Sleiti et al., 2021), combined water and cooling production systems (Sleiti et al., 2020b,a), oil and gas systems (Sleiti et al., 2020c), etc. The thermodynamic properties

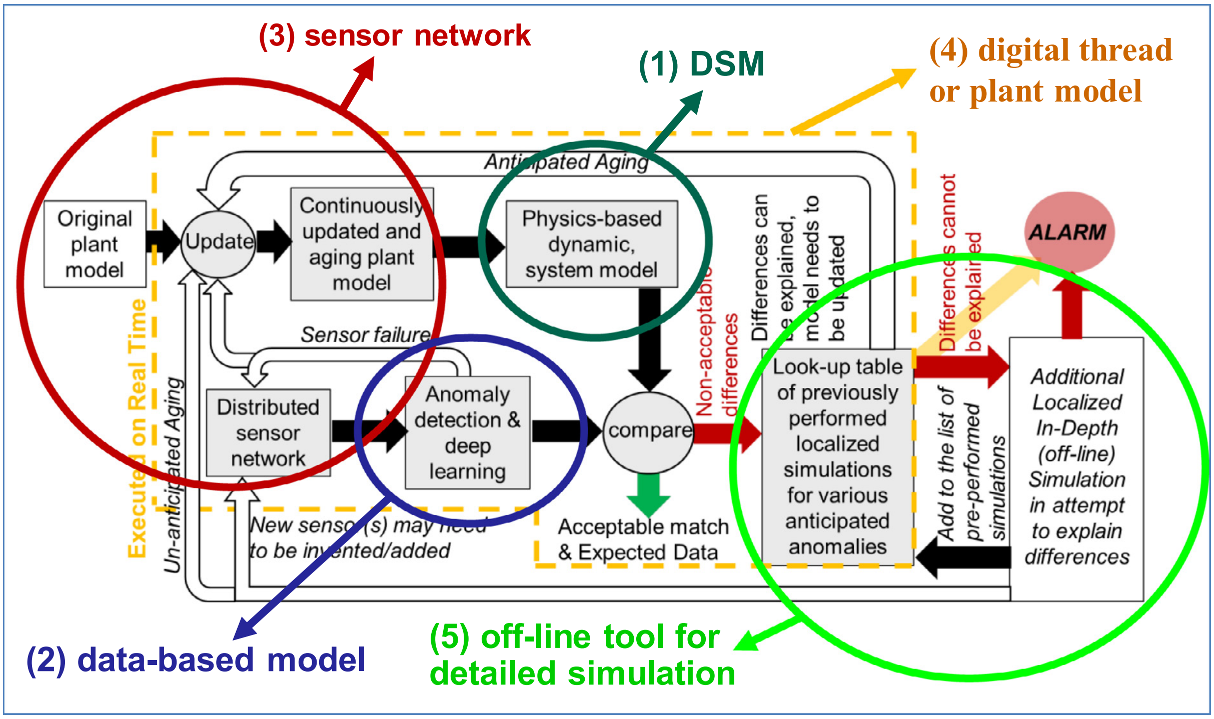


Fig. 11. The overall flowchart of the proposed power plant DT architecture.

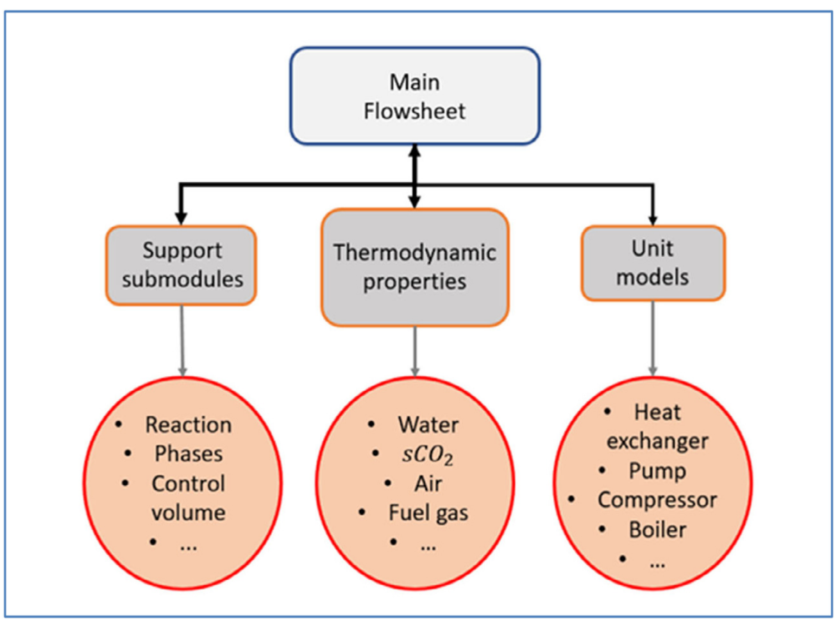


Fig. 12. IDAES flowsheet — example.

models define the purity or composition of the working medium, and its thermodynamic properties according to equations of state (EOS) for water (Wagner and Pruss, 2002; Wagner and Pruß, 2002; Wagner et al., 2000; AKASAK, 2008; Huber et al., 2012; Daucik and Dooley, 2011; Huber et al., 2009), and for flue gas or CO_2 (Span and Wagner, 1996; Vesovic et al., 1990; Fenghour et al., 1998). The models also define how, and which parameters are necessary for calculation of thermodynamic properties. The properties are calculated from two independent parameters, temperature and pressure. The main thermodynamic properties, which the models can calculate and give for optimization are the enthalpy, entropy, thermal conductivity, kinematic and dynamic viscosity.

(2) Data-based model; Anomaly Detection and deep Learning (ADL)

Beside the DMS the DT architecture includes data-based model, which uses real-time data from a system. The data-based model uses Anomaly Detection and deep Learning (ADL) for the detection of the difference between DSM and ADL, which can be traced back to sensor failure(s), then the sensor database and the DT database or digital thread of the system are updated, see Fig. 13. Unlike DMS, which is based on a physical description of

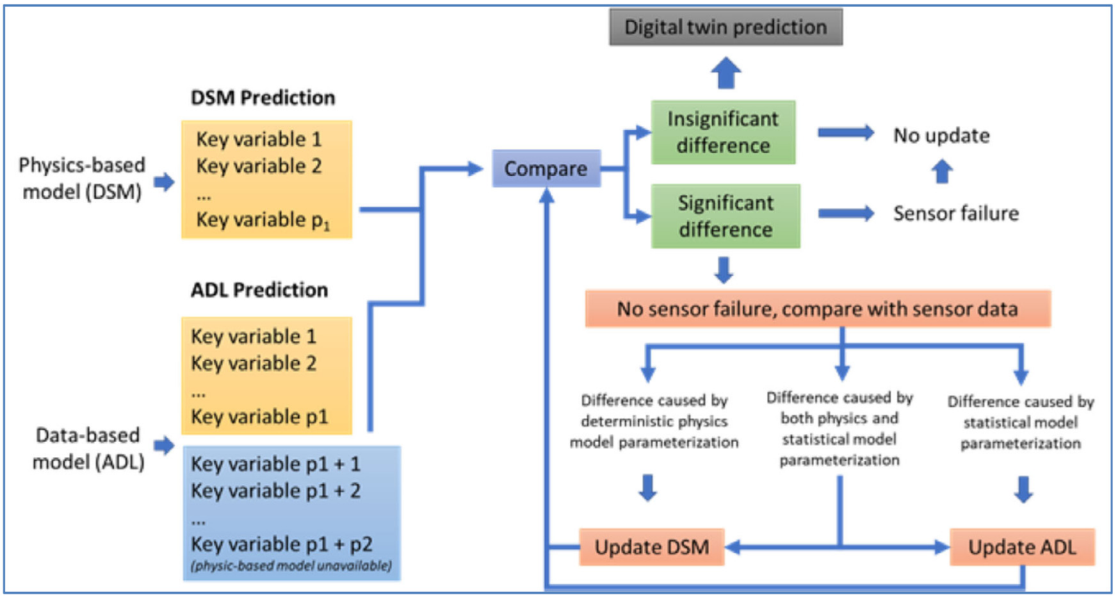


Fig. 13. The ADL algorithm approach and DSM prediction of the DT architecture.

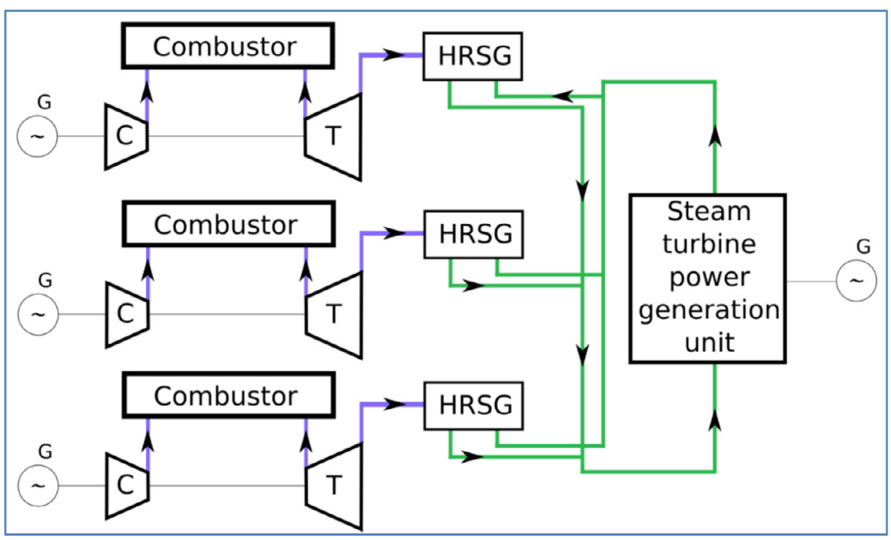


Fig. 14. Power plant schematic, based on Goyal et al. (2019).

the system, ADL uses statistical methods to find dependence. For data-based model, a few approaches are suggested using various advanced techniques in ML/DL/AI that can be utilized for this purpose:

- The ADL algorithm approach, which uses real data from power plants. This data can be sorted using multiple statistical tools.
- The generalized additive models (GAMs), which lends insight into the understanding of the non-linear relationship between the system inputs (e.g., fuel flow, etc.) and outputs (e.g., temperature, power, etc.) of the system, Granger (1969), Goyal et al. (2019).
- Multiple-stage vector autoregressive model (VAR) can be used in which, a variable present value is expressed as linear combination of other variables' previous values or itself. For a factor not explainable by its historical value, a random error term can be used, Lütkepohl (2005), Goyal et al. (2019, 2020).

An example to demonstrate the advantages of ADL of Fig. 13, is the case of using vector autoregressive model for anomaly detection in utility gas turbines (Goyal et al., 2019), Fig. 14. In this example, an operational power-plant data is used. Such power plant has 3 identical gas turbine (GT) units, one entire steam turbine (ST), and 3 heat recovery steam generator (HRSG) units as shown in Fig. 15.

The data for the analysis, according to Fig. 14, comes from only one of the GTs, HRSG and ST. Several anomalies are detected and reported during operation via controlled false alarms that are treated using physics-based methods to determine if an action needs to be taken. In this example, the DT architecture summarizes a pure data-driven statistical autoregression study that uses the behavior of the past values of the system to predict future values to help figuring out if the measurement data are in the toleration or show anomalies. When some values deviate from the autoregression, they are flagged as an anomaly, however large number of false alarms mean that such a method is ineffective. A demonstration of this method is provided by Fig. 15 for a combined cycle power generation and the pressure of the

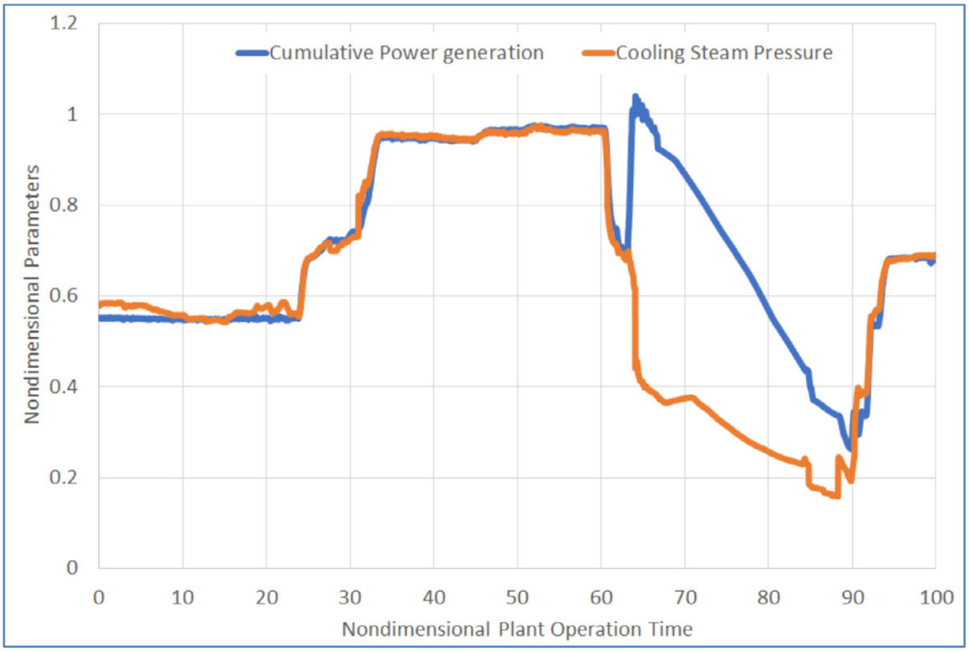


Fig. 15. Unexpected change in the pressure of the cooling steam, based on Goyal et al. (2019).

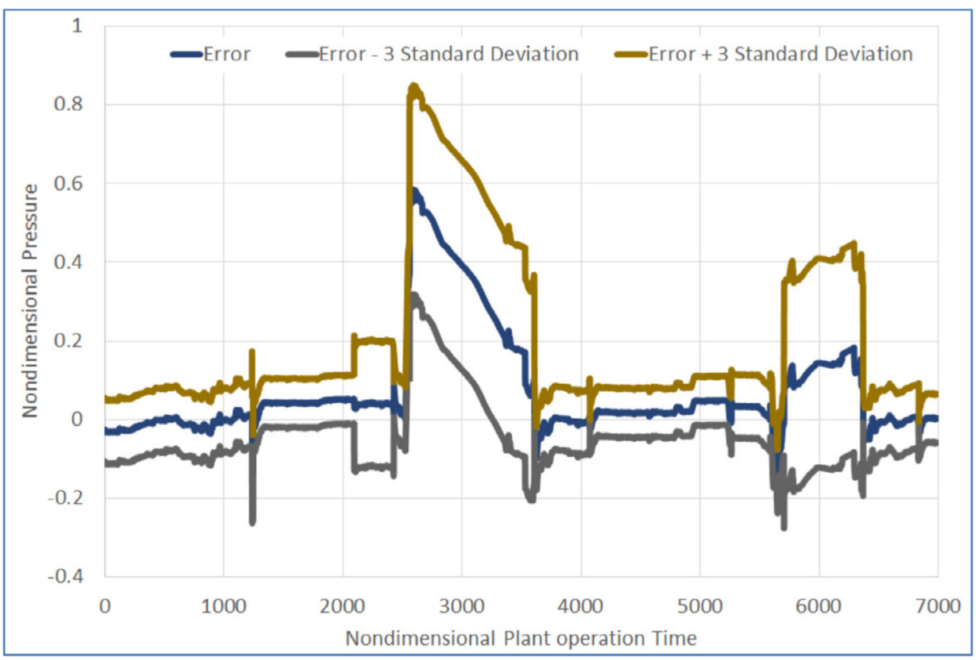


Fig. 16. In advance prediction error in cooling steam pressure, based on Goyal et al. (2019).

cooling steam in one of the GT units. The noticeable increase in the cooling pressure at the nondimensional time of about 90 is flagged as an anomaly as seen in Fig. 15 and hence actions can be taken before causing unit failure by this anomaly.

A multiple-stage vector autoregressive model, in the above example, is constructed for the nominal operation of the power plant assuming that the variables are initially correlated and then the anomaly detection/prediction is based on this assumption. The prediction is compared with the plant operation time-series data that have anomalies. Granger causality networks, based on the associations between the time series streams, are found as an implication from the vector autoregressive modeling. The anomaly is detected via comparing the observed measurements with the predicted values. The details of this methodology can be found in Goyal et al. (2019).

Fig. 16 shows the in advance prediction for different ranges of cooling steam pressure over the testing period, including both states "off" and "on". The prediction error is presented with 3 standard deviations of the corresponding stages. The sudden increase around time 90 shows a non-negligible prediction error, indicating abnormal behavior of the pressure of the cooling steam from its normal values. The 3 standard deviations of the prediction error excludes the possibility that the deviations are just noise.

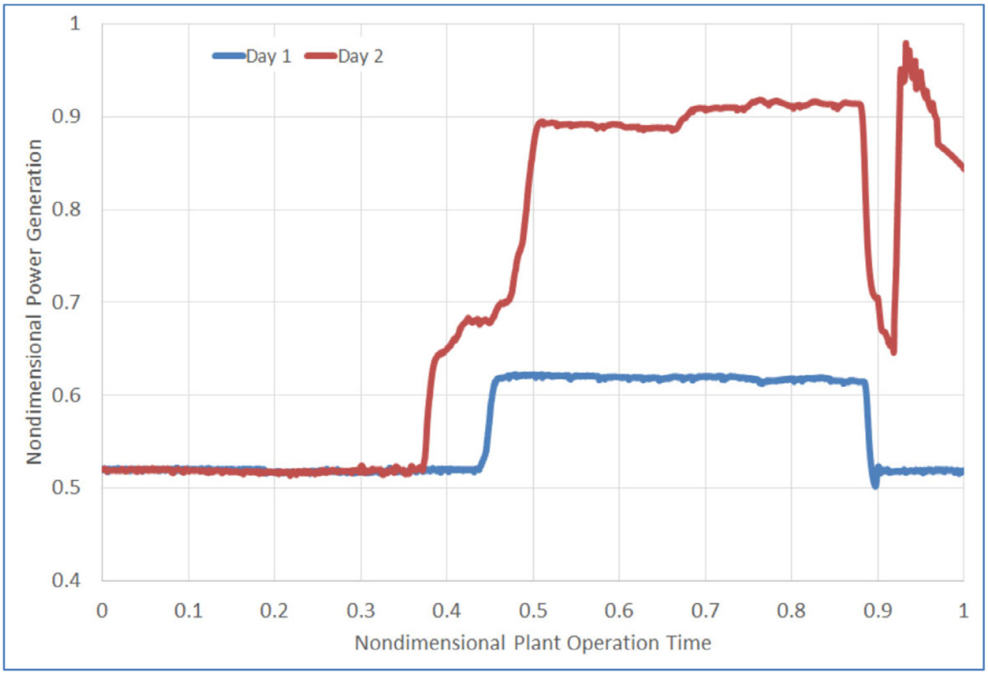


Fig. 17. The power generation failure – real-time measurement, based on Goyal et al. (2019).

(3) Sensor network and data sources:

A power plant simulator flow loop (available from different sources) can be used for public domain data for initial model development and debugging. The system imports streaming data from temperature sensors, vibration sensors, pressure sensors and accelerometers and other subsystems of the simulated power plant. The level of data influx from different temperature sensors, pressure sensors, and other parts of sub systems is very large. As an example, Fig. 17 shows real data from the power plant, mentioned in Fig. 14, for two different days, which are used in ADL. To reduce the size of this "Big Data" from sensors, "Data Analytics" can be used (Tannahill and Jamshidi, 2014) that implement computational intelligence (CI) and statistical tools such as clustering, principal component analysis (PCA), neuro-computing, genetic algorithms, Bayesian networks, fuzzy logic, etc. A demonstration is provided in Tannahill and Jamshidi (2014) of using such data analytics to generate models to forecast produced PV energy to optimize micro grids.

The Distributed Sensor Network (DSN) provides real-time readings of the system parameters. It forms the basis of the data to be used by ADL, see Fig. 11. As existing sensors fail, DSN database needs to be updated. As new failure mechanisms are understood and corresponding sensors are implemented, DSN database also needs to be updated. Assessment of sensors' reliability is very important as discussed in Castaño et al. (2019) that proposed a co-simulation framework to enable real-time interaction between virtual and real sensors.

(4) System Genome or Digital Thread:

The digital thread component of the proposed DT must be updated initially and then continuously, according to Fig. 11. The power plant model must also include the initial manufacturing or as-manufactured deviations from the design intent. A central feature of any DT architecture is the consideration of "aging" or continuous system deterioration. DT architecture must age the same way as the physical twin will.

(5) Localized in-Depth Simulations (LDS):

LDS are required when the physics-based model and the data-based model disagree with each other, according to Figs. 10 and 11, and when we need to understand basic underlying physical phenomenon using software where analytical methods are not precise. This is because data-based algorithms tend to look for systematic patterns and physics-based reasoning is required to remove spurious correlations and false patterns. Unacceptable levels of disagreement will force the digital twin algorithm to look-up a collection of pre-performed localized in-depth simulations (LDS) of various components of the system. When no such pre-performed simulation is available, a new one will be performed, and the results will be added to the look-up collection for future usage as well. The LDS can be performed using appropriate commercial or open-source CFD, FEM, Acoustics, etc. software.

4.4. Future work for the proposed DT for power plants

The DT architecture development for power plants and similar systems is a very complex procedure that needs to be identified, defined, and decided according to real data and physical description of the system. With the above 5 different parts of DT, which are connected to each other, the future work on the DT architecture would be focused on each part individually and on the overall connections. The auto regression model example (presented in this section earlier) that was used to detect anomalous behavior, performs better when the system is not dynamic and as such, the future research should concentrate on algorithms that are capable of predicting the system's dynamic behavior with data-driven methods.

Data-driven approaches alone, (AD in Fig. 10) are not sufficient for a robust DT that supposed to predict failures in advance to trigger corrective actions, rather a multi-faceted approach is needed. Additionally, for interpreting and enhancing the results from the data driven process, a physics based model (low order DSM in Figs. 10 and 11), should operate in tandem with the latest system parameters.

The comparisons, validations and verifications are continuous processes, and as such, the unexplainable discrepancy between DSM and ADL, requires off-line in-depth localized simulations (LDS in Fig. 10). Such simulations would identify the causes of the discrepancies between ADL and DSM. The addition or not of sensors at strategic-critical locations to the DSN, can be determined from the results of LDS.

Power plants operate almost continuously, which causes degradations in the parameters used in the ADL. For this reason, the data set that defines the system parameters (System Genome in Fig. 10), should be updated all the time. This can be done either via measurements or through parameter estimation applied to data from sensors.

For robust DT architecture, the DT must not be based only on ADL or data driven processes, rather the 5 components; DSM, DSN, ADL, LDS and System Genome, should be integrated.

5. Conclusions

Digital twins can transform the energy production sector and can meaningfully improve the energy efficiency in industrial, buildings, service, and transportation sectors. The integration of renewable energy in the energy production sector makes the future power plants more complex that will require DT architecture to achieve high reliability, availability and maintainability (RAM) at lower cost. However, applications of DTs for power plants are unusually limited in open literature, suggesting that tremendous research opportunities in the field are still wide open.

In the present study the use of DT for power plants and its potential to transform the energy production industry is investigated. The main contributions of the present work include: an overview of DT key research related to power plants including applications, frameworks and architectures; an overview of DT key research and development for energy savings applications that benefits the development of PPDT; and proposing new robust DT architecture for power plants, and other similar complex capital-intensive large engineering systems.

The requirements and rules for developing PPDT are established first and then used to develop the proposed PPDT that consists of five key components. These DT architecture components are: DSM or physics-based formulations of a system of interest (power plant, air craft, storage, etc.), ADL or statistical analysis of data from the sensor network, as well as DNS or real-time data of a system of interest and LDS or pre-performed localized in-depth simulations to predict activities of the corresponding physical twin. All these four components are connected to the system Genome with a digital thread.

The present study also suggests the future directions for DT architecture development for power plants and similar complex systems. The DT development needs real data and physical description of the overall system with focus on each part of the system individually and on the overall connections. Algorithms that are capable of predicting the dynamic behavior of the system with data-driven methods still need more advanced development. Data-driven approach alone is not sufficient and a physics based (low order) model DSM must be operated in tandem with the latest system parameters, to enhance and interpret the results from the data driven process. Discrepancy between DSM and ADL, will require in-depth localized off-line simulation (LDS). All five components of the proposed DT architecture, DSM, DSN, ADL, LDS and System Genome, should be integrated to achieve a robust DT.

Lastly, it was observed that research related to the importance of integration of energy systems cyber security with DTs has not been reported in open literature (only couple studies listed in Table 2), which makes this subject a priority for future research.

CRediT authorship contribution statement

Ahmad K. Sleiti: Conceptualization, Investigation, Writing – original draft, Writing – review & editing, Funding acquisition, Supervision. **Jayanta S. Kapat:** Conceptualization, Project administration, Supervision, Visualization. **Ladislav Vesely:** Conceptualization, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

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

Acknowledgments

The work presented in this publication was made possible by NPRP-S grant # [11S-1231-170155] from the Qatar National Research Fund (a member of Qatar Foundation). The findings herein reflect the work, and are solely the responsibility, of the authors.

References

AKASAK, R.A., 2008. A reliable and useful method to determine the saturation state from Helmholtz energy equations of state. J. Therm. Sci. Technol. http://dx.doi.org/10.1299/jtst.3.442.

Al-Ali, A.R., Gupta, R., Batool, T.Z., Landolsi, T., Aloul, F., Al Nabulsi, A., 2020. Digital twin conceptual model within the context of internet of things. Futur. Internet http://dx.doi.org/10.3390/fi12100163.

Andoni, M., Robu, V., Flynn, D., Abram, S., Geach, D., Jenkins, D., et al., 2019. Blockchain technology in the energy sector: A systematic review of challenges and opportunities. Renew. Sustain. Energy Rev. 100, 143–174. http://dx.doi.org/10.1016/j.rser.2018.10.014.

Andryushkevich, S.K., Kovalyov, S.P., Nefedov, E., 2019. Composition and application of power system digital twins based on ontological modeling. IEEE Int. Conf. Ind. Informatics http://dx.doi.org/10.1109/INDIN41052.2019.8972267.

Anton, F., Borangiu, T., Răileanu, S., Anton, S., 2020. Cloud-based digital twin for robot integration in intelligent manufacturing systems. Mech. Mach. Sci. http://dx.doi.org/10.1007/978-3-030-48989-2_60.

Armendia, Mikel., Ghassempouri, Mani., Erdem Ozturk, F.P., 2004. Twin-control a digital twin approach to improve machine tools lifecycle. vol. 59. http://dx.doi.org/10.1097/01.fch.0000336108.22926.39.

Augustine, P., 2020. The industry use cases for the digital twin idea. Adv. Comput. http://dx.doi.org/10.1016/bs.adcom.2019.10.008.

Barszcz, T., Zabaryłło, M., 2019. Concept of automated malfunction detection of large turbomachinery using machine learning on transient data. Diagnostyka http://dx.doi.org/10.29354/diag/100399.

Bayer, V., Kunath, S., Niemeier, R., Horwege, J., 2018. Signal-based metamodels for predictive reliability analysis and virtual testing. Adv. Sci. Technol. Eng. Syst. http://dx.doi.org/10.25046/aj030141.

Bondarenko, O., Fukuda, T., 2020. Development of a diesel engine's digital twin for predicting propulsion system dynamics. Energy 196, 117126. http://dx.doi.org/10.1016/j.energy.2020.117126.

Brannvall, R., Sarkinen, J., Svartholm, J., Gustafsson, J., Summers, J., 2019. Digital twin for tuning of server fan controllers. IEEE Int. Conf. Ind. Inf. http://dx.doi.org/10.1109/INDIN41052.2019.8972291.

Brosinsky, C., Krebs, R., Westermann, D., 2020. Embedded digital twins in future energy management systems: paving the way for automated grid control. At-Automatisierungstechnik http://dx.doi.org/10.1515/auto-2020-0086.

Brosinsky, C., Westermann, D., Krebs, R., 2018. Recent and prospective developments in power system control centers: Adapting the digital twin technology for application in power system control centers. In: 2018 IEEE Int. Energy Conf. ENERGYCON 2018. http://dx.doi.org/10.1109/ENERGYCON.2018.8398846.

Bureau of Energy Efficiency (BEE) M. of P.G. of I, 2018. Enhancing energy efficiency through industry partnership. vol. 4.

Cardin, O., Castagna, P., Couedel, D., Plot, C., Launay, J., Allanic, N., et al., 2020. Energy-aware resources in digital twin: The case of injection moulding machines. Stud. Comput. Intell. http://dx.doi.org/10.1007/978-3-030-27477-1_14.

Carrillo Peña, A.L., Eugenio Barroso, J.S., Martínez Vesga, A.A., Roa Prada, S., Ardila Acuña, V.A., 2019. Improving the performance of centrifugal pumps in serial and parallel configurations using digital twins. ASME Int. Mech. Eng. Congr. Expo. Proc. http://dx.doi.org/10.1115/IMECE2019-12038.

Castaño, F., Strzełczak, S., Villalonga, A., Haber, R.E., Kossakowska, J., 2019. Sensor reliability in cyber–physical systems using internet-of-things data: A review and case study. Remote Sens. 11. http://dx.doi.org/10.3390/rs11192252.

Castagna, P., Allanic, N., Madec, Y., Jegouzo, S., Castagna, P., Couedel, D., et al., 2019. Energy-aware resources in digital twin: the case of injection molding machines to cite this version: HAL id: hal-02382494 energy-aware resources in digital twin: the case of injection molding machines to cite this version: HAL id: hal-02382494.

Center for Climate and Energy Solutions (C2ES), Global Emissions 2020. https://www.c2es.org/content/international-emissions/.

Chakrabortty, R.K., Rahman, H.F., Mo, H., Ryan, M.J., 2019. Digital twin-based cyber physical system for sustainable project scheduling. IEEE Int. Conf. Ind. Eng. Eng. Manag. http://dx.doi.org/10.1109/IEEM44572.2019.8978712.

Cimino, C., Negri, E., Fumagalli, L., 2019. Review of digital twin applications in manufacturing. Comput. Ind. 113, 103130. http://dx.doi.org/10.1016/j.compind.2019.103130.

Daucik, K., Dooley, R.B., 2011. Release on the IAPWS formulation 2011 for the thermal conductivity of ordinary water substance. Iapws.

Dawes, B., Meah, N., Kudryavtsev, A., Evans, R., Hunt, M., Tiller, P., 2019. Digital geometry to support a gas turbine digital twin. In: AIAA Scitech 2019 Forum. pp. 1–17. http://dx.doi.org/10.2514/6.2019-1715.

Dong, R., She, C., Hardjawana, W., Li, Y., Vucetic, B., 2019. Deep learning for hybrid 5G services in mobile edge computing systems: Learn from a digital twin. IEEE Trans. Wirel. Commun. 18, 4692–4707. http://dx.doi.org/10.1109/TWC.2019.2927312.

Ebrahimi, A., 2019. Challenges of developing a digital twin model of renewable energy generators. IEEE Int. Symp. Ind. Electron. 2019-June, 1059–1066. http://dx.doi.org/10.1109/ISIE.2019.8781529.

EED, 2012. Directive 2012/27/EU of the European parliament and of the council of 25 2012 on energy efficiency. Off. J. Eur. Union 1–56.

EIA, 2022. International energy outlook 2019. Report 2020. https://www.eia.gov/todayinenergy/detail.php?d=41433 (accessed February 7, 2022).

Errandonea, I., Beltrán, S., Arrizabalaga, S., 2020. Digital twin for maintenance: A literature review. Comput. Ind. http://dx.doi.org/10.1016/j.compind.2020.103316.

European Commission, 2020. Energy efficiency targets. https://ec.europa.eu/energy/topics/energy-efficiency/targets-directive-and-rules/eu-targets-energy-efficiency_en?redir=1#content-heading-0.

Fenghour, A., Wakeham, W.A., Vesovic, V., 1998. The viscosity of carbon dioxide. J. Phys. Chem. Ref. Data http://dx.doi.org/10.1063/1.556013.

Ferguson, S., Bennett, E., Ivashchenko, A., 2017. Digital twin tackles design challenges. World Pumps 2017, 26–28. http://dx.doi.org/10.1016/s0262-1762(17)30139-6.

Fuller, A., Fan, Z., Day, C., Barlow, C., 2020. Digital twin: Enabling technologies, challenges and open research. IEEE Access 8, 108952–108971. http://dx.doi.org/10.1109/ACCESS.2020.2998358.

Gaikwad, A., Yavari, R., Montazeri, M., Cole, K., Bian, L., Rao, P., 2020. Toward the digital twin of additive manufacturing: Integrating thermal simulations, sensing, and analytics to detect process faults. IISE Trans. http://dx.doi.org/10.1080/24725854.2019.1701753.

Glaessgen, E.H., Stargel, D.S., The digital twin paradigm for future NASA and U.S. air force vehicles. In: Collect Tech Pap - AIAA/ASME/ASCE/AHS/ASC Struct Struct Dyn Mater Conf 2012. pp. 1–14. http://dx.doi.org/10.2514/6.2012-1818.

Goyal, V., Xu, M., Kapat, J., 2019. Use of vector autoregressive model for anomaly detection in utility gas turbines. In: Proc. ASME Turbo Expo. http://dx.doi.org/10.1115/GT2019-90995.

Goyal, V., Xu, M., Kapat, J., Vesely, L., 2020. Gt2020-15232 prediction of gas turbine performance using machine learning methods. In: Proc. ASME Turbo Expo 2020 Turbomach. Tech. Conf. Expo. GT2020, 2020.

Granger, CWJ., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica http://dx.doi.org/10.2307/1912791.

Guerra, R.H., Quiza, R., Villalonga, A., Arenas, J., Castano, F., 2019. Digital twin-based optimization for ultraprecision motion systems with backlash and friction. IEEE Access 7, 93462–93472. http://dx.doi.org/10.1109/ACCESS.2019.2928141.

Gunter, K.D., Agarwal, D, A., Beattie, K, S., et al., 2018. Institute for the design of advanced energy systems process systems engineering framework (IDAES PSE framework). Computer Softw. http://dx.doi.org/10.11578/dc.20181030.4.

Gupta, A., Basu, B., 2019. Sustainable primary aluminium production: Technology status and future opportunities. Trans. Indian Inst. Met. http://dx.doi.org/10.1007/s12666-019-01699-9.

Hauf, D., Sus, S., Strahilov, A., Franke, J., 2017. Multifunctional use of functional mock-up units for application in production engineering. In: Proc. - 2017 IEEE 15th Int. Conf. Ind. Informatics, INDIN 2017. http://dx.doi.org/10.1109/INDIN.2017.8104925.

Howard, D.Anthony., Ma, Z., Aaslyng, J.Mazanti., Norregaard Jorgensen, B., 2020. Data architecture for digital twin of commercial greenhouse production. In: Proc. - 2020 RIVF Int. Conf. Comput. Commun. Technol. RIVF 2020. http://dx.doi.org/10.1109/RIVF48685.2020.9140726.

Howard, D.A., Ma, Z., Jørgensen, B.N., 2021. Digital twin framework for energy efficient greenhouse industry 4.0. Adv. Intell. Syst. Comput. http://dx.doi.org/10.1007/978-3-030-58356-9_34.

Huber, M.L., Perkins, R.A., A., Laesecke, D.G., Friend, Sengers, J.V., Assael, M.J., et al., 2009. New international formulation for the viscosity of H2O. J. Phys. Chem. Ref. Data http://dx.doi.org/10.1063/1.3088050.

Huber, M.L., Perkins, R.A., Friend, D.G., Sengers, J.V., Assael, M.J., Metaxa, I.N., et al., 2012. New international formulation for the thermal conductivity of H2O. J. Phys. Chem. Ref. Data http://dx.doi.org/10.1063/1.4738955.

IEA, 2018. Energy efficiency in China, IEA, Paris. https://www.iea.org/articles/energy-efficiency-in-china.

Jain, P., Poon, J., Singh, J.P., Spanos, C., Sanders, S.R., Panda, S.K., 2020. A digital twin approach for fault diagnosis in distributed photovoltaic systems. IEEE Trans. Power Electron. 35, 940–956. http://dx.doi.org/10.1109/TPEL.2019.2911594.

Jones, D., Snider, C., Nassehi, A., Yon, J., Hicks, B., 2020. Characterising the digital twin: A systematic literature review. CIRP J. Manuf. Sci. Technol. 29, 36–52. http://dx.doi.org/10.1016/j.cirpj.2020.02.002.

Kaewunruen, S., Rungskunroch, P., Welsh, J., 2018. A digital-twin evaluation of net zero energy building for existing buildings. Sustain 11, 1–22. http://dx.doi.org/10.3390/su11010159.

Kahlen, F.J., Flumerfelt, S., Alves, A., 2016. Transdisciplinary perspectives on complex systems: New findings and approaches. http://dx.doi.org/10.1007/978-3-319-38756-7.

Kannan, K., Arunachalam, N., 2019. A digital twin for grinding wheel: An information sharing platform for sustainable grinding process. J Manuf. Sci. Eng. Trans. ASME http://dx.doi.org/10.1115/1.4042076.

Karanjkar, N., Joglekar, A., Mohanty, S., Prabhu, V., Raghunath, D., Sundaresan, R., 2019. Digital twin for energy optimization in an SMT-PCB assembly line. In: Proc - 2018 IEEE Int Conf Internet Things Intell Syst IOTAIS 2018. pp. 85–89. http://dx.doi.org/10.1109/IOTAIS.2018.8600830.

Klein, H., Fritsch, P., Haider, P., Kender, R., Rößler, F., Rehfeldt, S., et al., 2020. Flexible operation of air separation units. Chemie-Ingenieur-Technik http://dx.doi.org/10.1002/cite.202000054.

Kozhevnikov, M.V.Gitelman.L.D., Kaplin, D.D., 2019. Asset management in grid companies using integrated diagnostic devices. Int J Energy Prod Manag http://dx.doi.org/10.2495/EQ-V4-N3-230-243.

Kychkin, A., Deryabin, A., Vikentyeva, O., Shestakova, L., 2019. Architecture of compressor equipment monitoring and control cyber–physical system based on influxdata platform. In: 2019 Int. Conf. Ind. Eng. Appl. Manuf. ICIEAM 2019. http://dx.doi.org/10.1109/ICIEAM.2019.8742963.

Kychkin, A., Nikolaev, A., 2020. Iot-based mine ventilation control system architecture with digital twin. In: Proc. - 2020 Int. Conf. Ind. Eng. Appl. Manuf. ICIEAM 2020. http://dx.doi.org/10.1109/ICIEAM48468.2020.9111995.

Li, W., Rentemeister, M., Badeda, J., Jöst, D., Schulte, D., Sauer, D.U., 2020. Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation. J. Energy Storage http://dx.doi.org/10.1016/j.est.2020.101557.

Lin, L., Athe, P., Rouxelin, P., Avramova, M., Gupta, A., Youngblood, R., et al., 2021. Development and assessment of a nearly autonomous management and control system for advanced reactors. Ann. Nucl. Energy http://dx.doi.org/10.1016/j.anucene.2020.107861.

Liu, M., Fang, S., Dong, H., Xu, C., 2020. Review of digital twin about concepts, technologies, and industrial applications. J. Manuf. Syst. 1–16. http://dx.doi.org/10.1016/j.jmsy.2020.06.017.

Liu, D., Huang, H., Wang, B., Zhou, T., Luo, S., 2019. Operation paradigm for remanufacturing shop-floor based on digital twin. Jisuanji Jicheng Zhizao Xitong/Computer Integr. Manuf. Syst. CIMS http://dx.doi.org/10.13196/j.cims.2019.06.019.

Loboda, I., 2016. Neural networks for gas turbine diagnosis. Artif. Neural. Networks - Model. Appl. http://dx.doi.org/10.5772/63107.

Lu, H., Huang, K., Azimi, M., Guo, L., 2019. Blockchain technology in the oil and gas industry: A review of applications, opportunities, challenges, and risks. IEEE Access 7, 41426–41444. http://dx.doi.org/10.1109/ACCESS.2019.2907695.

Lu, Y., Liu, C., Wang, K.I.K., Huang, H., Xu, X., 2020a. Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robot Comput. Integr. Manuf. http://dx.doi.org/10.1016/j.rcim.2019.101837.

Lu, Q., Xie, X., Parlikad, A.K., Schooling, J.M., 2020b. Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance. Autom Constr. 118, 103277. http://dx.doi.org/10.1016/j.autcon.2020.103277.

Lund, A.M., 2018. Digital twin interface for operating wind farms. Eur. Pat. Appl. 1, 1–18.

Lütkepohl, H., 2005. New introduction to multiple time series analysis. http://dx.doi.org/10.1007/978-3-540-27752-1.

Lydon, G.P., Caranovic, S., Hischier, I., Schlueter, A., 2019. Coupled simulation of thermally active building systems to support a digital twin. Energy Build 202, 109298. http://dx.doi.org/10.1016/j.enbuild.2019.07.015.

Madni, A., Madni, C., Lucero, S., 2019. Leveraging digital twin technology in model-based systems engineering. Systems 7, 7. http://dx.doi.org/10.3390/systems7010007.

Máša, V., Stehlík, P., Touš, M., Vondra, M., 2018. Key pillars of successful energy saving projects in small and medium industrial enterprises. Energy 158, 293–304. http://dx.doi.org/10.1016/j.energy.2018.06.018.

Mateev, M., 2020. Industry 4.0 and the digital twin for building industry. Int. Sci. J. Ind. 40.

Mayani, M.Gholami., Svendsen, M., Oedegaard, S.I., 2018. Drilling digital twin success stories the last 10 years. In: Soc. Pet. Eng. - SPE Norw. One Day Semin. 2018.

Merkle, L., 2019. Cloud-based battery digital twin middleware using model-based development. ACM Int. Conf. Proceeding Ser http://dx.doi.org/10.1145/3386164.3387296.

Ministry of Energy Green Technology and Water, 2015. National energy efficiency action plan. Natl. Energy Effic. 24.

Mitsubishi Heavy Industries, 2018. Boiler digital twin applying machine learning. Mitsubishi Heavy Ind. Tech. Rev. 55 (4), 1–7.

Moussa, C., Al-Haddad, K., Kedjar, B., Merkhouf, A., 2018. Insights into digital twin based on finite element simulation of a large hydro generator. In: Proc IECON 2018-44th Annu Conf IEEE Ind Electron Soc. pp. 553–558. http://dx.doi.org/10.1109/IECON.2018.8591653.

Mukherjee, T., DebRoy, T., 2019. A digital twin for rapid qualification of 3D printed metallic components. Appl. Mater. Today. 14, 59–65. http://dx.doi.org/10.1016/j.apmt.2018.11.003.

Negri, E., Assiro, G., Caioli, L., Fumagalli, L., 2019a. A machine state-based digital twin development methodology. Proc. Summer Sch. Fr. Turco..

Negri, E., Fumagalli, L., Cimino, C., MacChi, M., 2019b. FMU-supported simulation for CPS digital twin. Procedia Manuf. 28, 201–206. http://dx.doi.org/10.1016/j.promfg.2018.12.033.

Negri, E., Fumagalli, L., Macchi, M., 2017. A review of the roles of digital twin in CPS-based production systems. Procedia Manuf. 11, 939–948. http://dx.doi.org/10.1016/j.promfg.2017.07.198.

Oñederra, O., Asensio, F.J., Eguia, P., Perea, E., Pujana, A., Martinez, L., 2019. Mv cable modeling for application in the digital twin of a windfarm. In: ICCEP 2019-7th Int. Conf. Clean Electr. Power Renew. Energy Resour. Impact. http://dx.doi.org/10.1109/ICCEP.2019.8890166.

O'Dwyer, E., Pan, I., Charlesworth, R., Butler, S., Shah, N., 2020. Integration of an energy management tool and digital twin for coordination and control of multi-vector smart energy systems. Sustain. Cities Soc. 62, 102412. http://dx.doi.org/10.1016/j.scs.2020.102412.

Okita, T., Kawabata, T., Murayama, H., Nishino, N., Aichi, M., 2019. A new concept of digital twin of artifact systems: synthesizing monitoring/inspections, physical/numerical models, 935 and social system models. Procedia CIRP 79, 667–672. http://dx.doi.org/10.1016/j.procir.2019.02.048.

Open Knowledge Repository, 2020. Delivering energy efficiency in the middle east and north africa: Achieving energy efficiency potential in the industry, services and residential sectors.

Oyekan, J.O., Hutabarat, W., Tiwari, A., Grech, R., Aung, M.H., Mariani, M.P., et al., 2019. The effectiveness of virtual environments in developing collaborative strategies between industrial robots and humans. Robot Comput. Integr. Manuf. http://dx.doi.org/10.1016/j.rcim.2018.07.006.

Pairet, È., Ardón, P., Liu, X., Lopes, J., Hastie, H., Lohan, K.S., 2019. A digital twin for human-robot interaction. ACM/IEEE Int. Conf. Human-Robot Interact 372. http://dx.doi.org/10.1109/HRI.2019.8673015.

Park, J., Bae, K.T., Kim, D., Jeong, W., Nam, J., Lee, M.J., et al., 2021. Unraveling the limitations of solid oxide electrolytes for all-solid-state electrodes through 3D digital twin structural analysis. Nano Energy http://dx.doi.org/10.1016/j.nanoen.2020.105456.

Park, H.A., Byeon, G., Son, W., Jo, H.C., Kim, J., Kim, S., 2020a. Digital twin for operation of microgrid: Optimal scheduling in virtual space of digital twin. Energies http://dx.doi.org/10.3390/en13205504.

Park, K.T., Lee, D., Noh, S. Do, 2020b. Operation procedures of a work-center-level digital twin for sustainable and smart manufacturing. Int. J. Precis Eng. Manuf. - Green Technol. http://dx.doi.org/10.1007/s40684-020-00227-1.

Patterson, E.A., Taylor, R.J., Bankhead, M., 2016. A framework for an integrated nuclear digital environment. Prog. Nucl. Energy 87, 97–103. http://dx.doi.org/10.1016/j.pnucene.2015.11.009.

Peng, Y., Wang, H., 2019. Application of digital twin concept in condition monitoring for DC-dc converter. In: 2019 IEEE Energy Convers. Congr. Expo. ECCE 2019. http://dx.doi.org/10.1109/ECCE.2019.8912199.

Pileggi, P., Verriet, J., Broekhuijsen, J., Leeuwen, C.Van., Wijbrandi, W., Konsman, M., 2019. A digital twin for cyber–physical energy systems. In: 7th Work. Model. Simul. Cyber-Physical Energy Syst. MSCPES 2019 - Held As Part CPS Week, Proc. http://dx.doi.org/10.1109/MSCPES.2019.8738792.

Pombo, I., Godino, L., Sánchez, J.A., Lizarralde, R., 2020. Expectations and limitations of cyber–physical systems (CPS) for advanced manufacturing: A view from the grinding industry. Futur. Internet http://dx.doi.org/10.3390/FI12090159.

Qi, Q., Tao, F., Hu, T., Anwer, N., Liu, A., Wei, Y., et al., 2019. Enabling technologies and tools for digital twin. J. Manuf. Syst. 0–1. http://dx.doi.org/10.1016/j.jmsy.2019.10.001.

Rivas, D., Quiza, R., Rivas, M., Haber, R.E., 2020. Towards sustainability of manufacturing processes by multiobjective optimization: A case study on a submerged arc welding process. IEEE Access 8, 212904–212916. http://dx.doi.org/10.1109/ACCESS.2020.3040196.

Rocca, R., Rosa, P., Sassanelli, C., Fumagalli, L., Terzi, S., 2020. Integrating virtual reality and digital twin in circular economy practices: A laboratory application case. Sustain 12. http://dx.doi.org/10.3390/su12062286.

Saad, A., Faddel, S., Mohammed, O., 2020a. Iot-based digital twin for energy cyber-physical systems: Design and implementation. Energies 13, 4762. http://dx.doi.org/10.3390/en13184762.

Saad, A., Faddel, S., Youssef, T., Mohammed, O.A., 2020b. On the implementation of IoT-based digital twin for networked microgrids resiliency against cyber attacks. IEEE Trans Smart Grid http://dx.doi.org/10.1109/TSG.2020.3000958.

Scheibe, C., Semerow, A., Menke, J., Seta, P.La., Raab, A., Mehlmann, G., et al., 2019. A novel co-simulation concept using interprocess communication in shared memory. IEEE Power Energy Soc. Gen. Meet. http://dx.doi.org/10.1109/PESGM40551.2019.8973964.

Shrouf, F., Gong, B., Ordieres-Meré, J., 2017. Multi-level awareness of energy used in production processes. J. Clean Prod. 142, 2570–2585. http://dx.doi.org/10.1016/j.jclepro.2016.11.019.

Sivalingam, K., Sepulveda, M., Spring, M., Davies, P., 2018. 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: Proc - 2018 2nd Int Conf Green Energy Appl ICGEA 2018. pp. 197–204. http://dx.doi.org/10.1109/ICGEA.2018.8356292.

Sládek, P., Maryška, M., 2018. The business potential of emerging technologies in the energy industry domain. In: IDIMT 2018 Strateg. Model. Manag. Econ. Soc. - 26th Interdiscip. Inf. Manag. Talks.

Sleiti, A.K., Al-ammari, W., Ahmed, S., Kapat, J., 2021. Direct-fired oxy-combustion supercritical-CO2 power cycle with novel preheating configurations -thermodynamic and exergoeconomic analyses. Energy 226, 120441. http://dx.doi.org/10.1016/j.energy.2021.120441.

Sleiti, A.K., Al-ammari, W.A., Al-khawaja, M., 2020a. A novel solar integrated distillation and cooling system – design and analysis. Sol. Energy 206, 68–83. http://dx.doi.org/10.1016/j.solener.2020.05.107.

Sleiti, A.K., Al-Ammaria, W.A., Al-Khawaja, M., Karbon, M., 2020b. A combined thermo-mechanical refrigeration system with isobaric expander-compressor unit powered by low grade heat - design and analysis. Int. J. Refrig. http://dx.doi.org/10.1016/j.ijrefrig.2020.08.017.

Sleiti, A.K., Takalkar, G., El-Naas, M.H., Hasan, A.R., Rahman, M.A., 2020c. Early gas kick detection in vertical wells via transient multiphase flow modelling: A review. J. Nat. Gas. Sci. Eng. 80, 103391. http://dx.doi.org/10.1016/j.jngse.2020.103391.

Song, Y., Shi, Y., Yu, J., Tang, D., Tao, F., 2019. Application of digital twin model in performance prediction of electro-optical detection system. Jisuanji Jicheng Zhizao Xitong/Computer Integr. Manuf. Syst. CIMS http://dx.doi.org/10.13196/j.cims.2019.06.023.

Span, R., Wagner, W., 1996. A new equation of state for carbon dioxide covering the fluid region from the triple-point temperature to 1100 K at pressures up to 800 MPa. J. Phys. Chem. Ref. Data http://dx.doi.org/10.1063/1.555991.

Stark, R., Damerau, T., 2019. Digital Twin. Int Acad Prod Eng Chatti S, Tolio T CIRP Encycl Prod Eng. Springer, Berlin, Heidelberg, pp. 1–8. http://dx.doi.org/10.1007/978-3-642-35950-7_16870-1.

Sun, H., Pan, J., Zhang, J., Mo, R., 2019. Digital twin model for cutting tools in machining process. Jisuanji Jicheng Zhizao Xitong/Computer Integr. Manuf. Syst. CIMS http://dx.doi.org/10.13196/j.cims.2019.06.015.

Talkhestani, B.Ashtari., Jung, T., Lindemann, B., Sahlab, N., Jazdi, N., Schloegl, W., et al., 2019. An architecture of an intelligent digital twin in a cyber-physical production system. At-Automatisierungstechnik 67, 762–782. http://dx.doi.org/10.1515/auto-2019-0039.

Tannahill, B.K., Jamshidi, M., 2014. System of systems and big data analytics - bridging the gap. Comput. Electr. Eng. 40, 2–15. http://dx.doi.org/10.1016/j.compeleceng.2013.11.016.

Tao, F., Zhang, M., Liu, Y., Nee, AYC., 2018. Digital twin driven prognostics and health management for complex equipment. CIRP Ann. 67, 169–172. http://dx.doi.org/10.1016/j.cirp.2018.04.055.

Tao, F., Zhang, H., Liu, A., Nee, AYC., 2019. Digital twin in industry: State-of-the-Art. IEEE Trans. Ind. Inf. 15, 2405–2415. http://dx.doi.org/10.1109/TII.2018.2873186.

Teng, S.Y., Touš, M., Leong, W.D., How, B.S., Lam, H.L., Máša, V., 2021. Recent advances on industrial data-driven energy savings: Digital twins and infrastructures. Renew. Sust. Energy Rev. 135. http://dx.doi.org/10.1016/j.rser.2020.110208.

Tharma, R., Winter, R., Eigner, M., 2018. An approach for the implementation of the digital twin in the automotive wiring harness field. Proc. Int. Des. Conf. Des. 6, 3023–3032. http://dx.doi.org/10.21278/idc.2018.0188.

Tong, X., Liu, Q., Pi, S., Xiao, Y., 2020. Real-time machining data application and service based on IMT digital twin. J. Intell. Manuf. 31, 1113–1132. http://dx.doi.org/10.1007/s10845-019-01500-0.

Uhlemann, T.H.J., Lehmann, C., Steinhilper, R., 2017. The digital twin: Realizing the cyber-physical production system for industry 4.0. Procedia CIRP 61, 335–340. http://dx.doi.org/10.1016/j.procir.2016.11.152.

Uhlemann, T.H.J., Schock, C., Lehmann, C., Freiberger, S., Steinhilper, R., 2017a. The digital twin: Demonstrating the potential of real time data acquisition in production systems. Procedia Manuf. 9, 113–120. http://dx.doi.org/10.1016/j.promfg.2017.04.043.

US Department of Energ, 2020. Advanced manufacturing office. https://www.energy.gov/eere/amo/advanced-manufacturing-office.

Vatankhah Barenji, A., Liu, X., Guo, H., Li, Z., 2020. A digital twin-driven approach towards smart manufacturing: reduced energy consumption for a robotic cellular. Int. J. Comput. Integr. Manuf. 00, 1–16. http://dx.doi.org/10.1080/0951192X.2020.1775297.

Vesovic, V., Wakeham, W.A., Olchowy, G.A., Sengers, J.V., Watson, J.T.R., Millat, J., 1990. The transport properties of carbon dioxide. J. Phys. Chem. Ref. Data http://dx.doi.org/10.1063/1.555875.

Volponi, A.J., 2014. Gas turbine engine health management: Past, present, and future trends. J. Eng. Gas Turbines Power http://dx.doi.org/10.1115/1.4026126.

Volponi, A.J., Tang, L., 2016. Improved engine health monitoring using full flight data and companion engine information. SAE Int. J. Aerosp. http://dx.doi.org/10.4271/2016-01-2024.

Wagner, W., Cooper, J.R., Dittmann, A., Kijima, J., Kretzschmar, H.J., Kruse, A., et al., 2000. The IAPWS industrial formulation 1997 for the thermodynamic properties of water and steam. J. Eng. Gas Turbines Power http://dx.doi.org/10.1115/1.483186.

Wagner, W., Pruß, A., 2002. The IAPWS formulation 1995 for the thermodynamic properties of ordinary water substance for general and scientific use. J. Phys. Chem. Ref. Data 31, 387–535. http://dx.doi.org/10.1063/1.1461829.

Wagner, W., Pruss, A., 2002. Revised release on the {iapws} formulation 1995 for the thermodynamic properties of ordinary water substance for general and scientific use. J. Phys. Chem. Ref. Data.

Wang, J., Huang, Y., Chang, Q., Li, S., 2019a. Event-driven online machine state decision for energy-efficient manufacturing system based on digital twin using Max-plus Algebra. Sustain http://dx.doi.org/10.3390/su11185036.

Wang, J., Ye, L., Gao, R.X., Li, C., Zhang, L., 2019b. Digital twin for rotating machinery fault diagnosis in smart manufacturing. Int. J. Prod. Res. 57, 3920–3934. http://dx.doi.org/10.1080/00207543.2018.1552032.

Weyer, S., Schmitt, M., Ohmer, M., Gorecky, D., 2015. Towards industry 4.0 - standardization as the crucial challenge for highly modular, multi-vendor production systems. IFAC-PapersOnLine 28, 579–584. http://dx.doi.org/10.1016/j.ifacol.2015.06.143.

Xiang, F., Huang, Y., Zhang, Z., Jiang, G., Zuo, Y., Tao, F., 2019. New paradigm of green manufacturing for product life cycle based on digital twin. Jisuanji Jicheng Zhizao Xitong/Computer Integr. Manuf. Syst. CIMS http://dx.doi.org/10.13196/j.cims.2019.06.018.

Xu, B., Wang, J., Wang, X., Liang, Z., Cui, L., Liu, X., et al., 2019. A case study of digital-twin-modelling analysis on power-plant-performance optimizations. Clean Energy 3, 227–234. http://dx.doi.org/10.1093/ce/zkz025.

Yan, K., Xu, W., Yao, B., Zhou, Z., Pham, D.T., 2018. Digital twin-based energy modeling of industrial robots. Commun. Comput. Inf. Sci. http://dx.doi.org/10.1007/978-981-13-2853-4_26.

Yu, J., Liu, P., Li, Z., 2020. Hybrid modelling and digital twin development of a steam turbine control stage for online performance monitoring. Renew. Sustain. Energy Rev. 133, 110077. http://dx.doi.org/10.1016/j.rser.2020.110077.

Yue, S., Jinsong, Y., Diyin, T., Xu, L., Jing, D., 2019. A dynamic bayesian network approach for electro-optical system performance monitoring digital twin. In: 2019 14th IEEE Int. Conf. Electron. Meas. Instruments, ICEMI, 2019. http://dx.doi.org/10.1109/ICEMI46757.2019.9101414.

Zhang, T., Liu, X., Luo, Z., Dong, F., Jiang, Y., 2019. Time series behavior modeling with digital twin for internet of vehicles. Eurasip J. Wirel. Commun. Netw. http://dx.doi.org/10.1186/s13638-019-1589-8.

Zhang, Y., Ma, S., Yang, H., Lv, J., Liu, Y., 2018a. A big data driven analytical framework for energy-intensive manufacturing industries. J. Clean Prod. 197, 57–72. http://dx.doi.org/10.1016/j.jclepro.2018.06.170.

Zhang, K., Qu, T., Zhou, D., Jiang, H., Lin, Y., Li, P., et al., 2020. Digital twin-based opti-state control method for a synchronized production operation system. Robot Comput. Integr. Manuf. 63, 101892. http://dx.doi.org/10.1016/j.rcim.2019.101892.

Zhang, M., Zuo, Y., Tao, F., 2018b. Equipment energy consumption management in applications. In: 2018 IEEE 15th Int Conf Networking, Sens Control. pp. 1–5.

Zhao, N., Wen, X., Li, S., 2016. A review on gas turbine anomaly detection for implementing health management. In: Proc. ASME Turbo Expo. http://dx.doi.org/10.1115/GT2016-58135.

Zitney, S.E., 2019. Dynamic model-based digital twin, optimization, and control technologies for improving flexible power plant operations. 3rd annu. Connect. Plant Conf. Charlotte, NC.