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Digital Twin Architectures for Predictive Maintenance of Electric and Gas Infrastructure

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Abstract: As plant equipment grows older and increasingly subject to the operational stresses of new distributed energy resources (DERs), pressure on electric and gas utilities is increasing to cut down on unplanned outages and to maximize asset life. The physics-based and data-driven virtual models are coupled with their physical counterparts via continuous bidirectional data propagation, forming digital twin architectures, a candidate framework for predictive maintenance in these areas. This paper presents a collection of 24 peer-reviewed papers published from 2018 to 2021 that discuss digital twin theory, reference architectures and domain applications related to electrical machines, distribution transformers, distributed photovoltaic (PV) systems, smart grid platforms, oil and gas production, and nearby mechanical and structural assets. The synthesis groups the literature into a five-dimensional reference model: physical, virtual, data, connection, and service dimensions, and illustrates how the dimensions are realised differently in the case of electric grid, gas and oil, and general industrial applications. A comparative overview shows that the majority of the studies reviewed focus on distribution level electric applications (eight), mechanical (seven) and predictive-maintenance (seven) topics, followed by general Industry 4.0 framework (five), structural infrastructure (three), and oil and gas applications (one). A field demonstration of a real-time digital twin is provided for a 678-kilowatt (kw) photovoltaic (PV) installation and a four-week industrial retrofitting case study to demonstrate the practicality of the approach. The synthesis also reveals that the 3 most often mentioned barriers to wider adoption are AI integration, cyber security and standardization. Finally, the paper states that digital twin architectures for electric and gas infrastructure are still in a relatively infancy stage of consolidation, and three key challenges across the sector for digital twin remain: data governance spanning the entire lifespan of a digital twin, model fidelity considerations, and the cross-vendor interoperability of digital twin.

***Keywords**: digital twin, predictive maintenance, electric grid, gas infrastructure, condition monitoring, smart grid, distributed energy resources, remaining useful life, Industry 4.0, cyber-physical systems, state estimation, artificial intelligence*

1. Introduction

Electric power and natural gas systems are among the most capital-intensive and safety-critical types of civil infrastructure and grow increasingly complex as they age, experience increasing distributed energy resource integration, and demand increasing levels of reliability from regulators and customers. Direct repair costs, prolonged outages, and in the case of a gas system, safety risks, as a result of unplanned failures of various electrical machines, pipeline components, transformers, and distribution feeders, have been a driving force in recent years as the industry has moved away from time and replacement-based maintenance and toward condition-based and predictive maintenance practices (Falekas & Karlis, 2021; Liu et al., 2018). A structured approach to associate a physical asset to a continually evolving virtual representation has been proposed by the digital twin concept, first introduced by Grieves with the domain of product lifecycle management and later formalized into a 5-dimensional model by Tao et al. (2019) with physical, virtual, service, data and connection dimensions. A digital twin is an architecture that allows for bidirectional, near real-time data exchange,

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with the virtual replica both capturing the current state of the physical system and, in some architectures, driving control actions back to the physical system, unlike a static simulation (Falekas & Karlis, 2021; Wagg et al., 2020). The most important feature that separates the digital twin from the other two seemingly similar but less comprehensive digital constructs—digital model and digital shadow—is that the digital twin can generate a return flow of data to the physical asset, whereas the digital model cannot, and the digital shadow may receive automated data from the physical asset with no return flow (Falekas & Karlis, 2021).

2. Conceptual Foundations of Digital Twin Architectures

The reviewed corpus of twenty-four studies is itself informative in the sense that the bulk of the publications has been concentrated in the two years of 2020 and 2021, with nineteen of the twenty-four sources reviewed being published in these two years, whereas one source in 2018 and four in 2019 have been published. This distribution results in the overall trend of digital twin research activity gaining significant momentum after the popularity of the five-dimensional reference model was explicitly highlighted by Falekas and Karlis (2021).

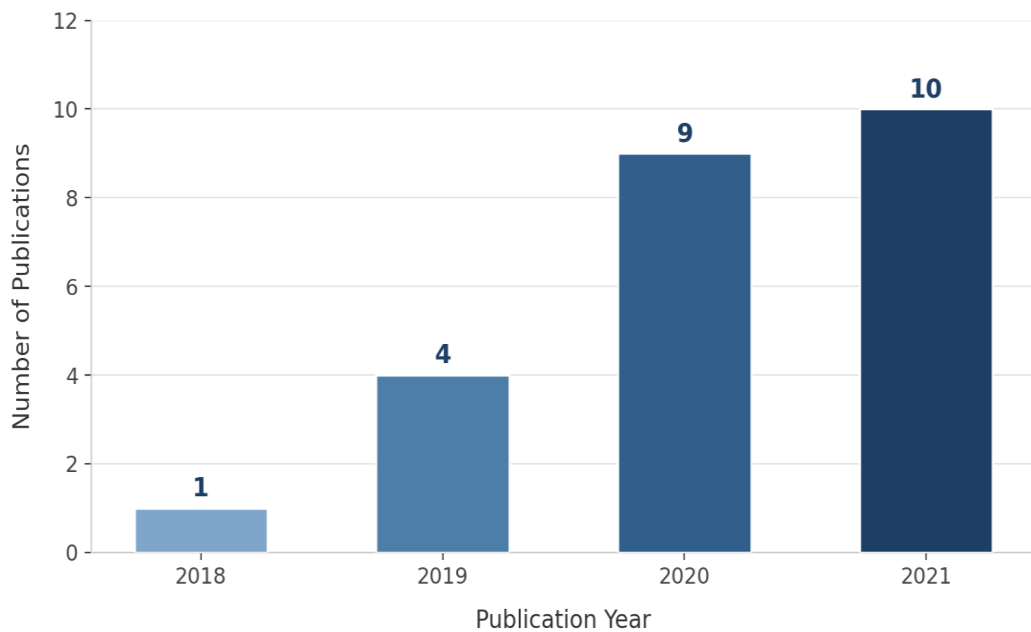

Figure 1. Publication-Year Distribution of the Reviewed Literature (N = 24 Studies)

2.1 Definitions and Dimensional Models

There have been many definitions since the inception of the digital twin and the reviewed literature shows this. According to the latest definition by the National Aeronautics and Space Administration (NASA) in 2012, the digital twin can be described as a multiphysics, multiscale and probabilistic simulation of the physical counterpart's state that integrates historical and real-time sensor data, and represents the state of the physical system with ultrafidelity.The latest definition by the National Aeronautics and Space Administration (NASA) in 2012 defines the digital twin as a multiphysics, multiscale, probabilistic, ultrafidelity simulation of the state of a physical counterpart that integrates historical and real-time sensor data. Later authors focused on using the twin as a living model that continuously adjusts to operational modifications and is able to anticipate the future action of the physical twin (Falekas & Karlis, 2021). Tao et al. (2019) expanded Grieves' original 3D formulation (physical entity, virtual entity, and the relationship between the two) into a 5D version with explicit data and service dimensions, which has since been followed in a variety of the articles in the reviewed corpus such as works on electrical machine predictive maintenance (Falekas & Karlis, 2021) and smart grid platforms (Jiang et al., 2021). The dimensions of the reference models identified in the literature are compared in Table 1. As the table shows, the three dimensions are intended to be expanded to make explicit the role of data handling, and other ancillary services like user interfaces and AI platforms and training utilities, that in previous three-dimensional

Table 1 **Comparison of Digital Twin Reference Model Dimensionalities Identified in the Reviewed Literature**

Model	Dimensions Included	Primary Emphasis	Representative Source
Three-dimensional (original)	Physical entity, virtual entity, connection	Basic physical-virtual mirroring	Grieves, as cited in Falekas & Karlis (2021)
Five-dimensional	Physical, virtual, service, data, connection	Explicit data handling and ancillary services	Tao et al. (2019)
Eight-dimensional (extended)	Five-dimensional set plus disaggregated data sub-layers	Fine-grained data lifecycle management	As reviewed in Falekas & Karlis (2021)
Lifecycle-phase model	Design, manufacturing, service, retire phases mapped onto the five dimensions	Full product lifecycle coverage	Falekas & Karlis (2021); Lu et al. (2020)

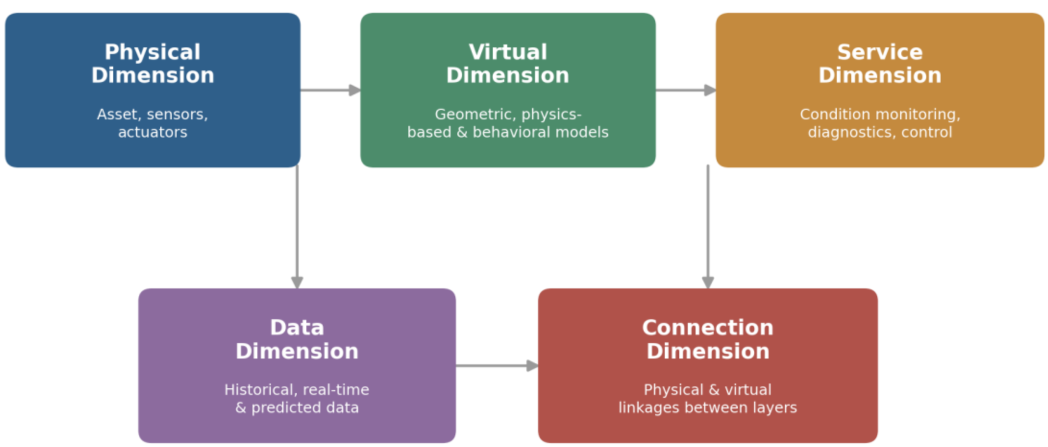

Figure 2. Five-Dimensional Digital Twin Reference Architecture

2.2 Lifecycle Integration and Data Sources

A recurring theme across the reviewed literature is that the value of a digital twin depends on its coverage of the complete asset lifecycle, spanning design, manufacturing, service, and retirement phases, rather than the service phase alone (Falekas & Karlis, 2021). Data generated during design and manufacturing, such as finite-element analysis results and factory-acceptance test records, can substantially accelerate the calibration of predictive maintenance models once an asset enters service, yet this information is frequently unavailable to maintenance engineers because of organizational silos between manufacturers and operators (Falekas & Karlis, 2021). Retirement-phase data is similarly neglected in most implementations, despite its potential value for informing the design of next-generation assets (Falekas & Karlis, 2021). Figure 2 depicts this circular lifecycle structure, in which a persistent data dimension links all four phases rather than being discarded when an asset changes hands or is decommissioned.

Figure 3. Digital Twin Lifecycle Integration Across Design, Manufacturing, Service, and Retirement Phases

Within the service phase, the reviewed literature consistently identifies three categories of data feeding the digital twin: historical records, real-time sensor streams, and model-derived or predicted values (Falekas & Karlis, 2021). Table 2 summarizes these categories together with representative examples drawn from the electric and gas infrastructure literature.

Table 2 **Digital Twin Data Categories and Representative Sources in Electric and Gas Infrastructure**

Data Category	Description	Representative Application
Historical	Archived maintenance records, prior fault events, factory test data	Remaining-useful-life estimation for electrical machines (Falekas & Karlis, 2021)

Data Category	Description	Representative Application
Real-time	Continuous sensor telemetry, SCADA feeds, advanced metering infrastructure	Low-voltage-side measurement of distribution transformers (Moutis & Alizadeh-Mousavi, 2021)
Model-derived / predicted	State-estimation outputs, simulation forecasts, prognostic indices	Distribution voltage regulation in telemetry-sparse feeders (Darbali-Zamora et al., 2021)

3. Digital Twin Architectures for Electric Grid Infrastructure

The number of studies dealing with electric power applications is largest among the studies reviewed, since eight of the 24 studies examined are related to electric power applications, as shown in Figure 3. These range from distribution-level component monitoring, distributed energy resource integration, to system-wide smart grid systems.

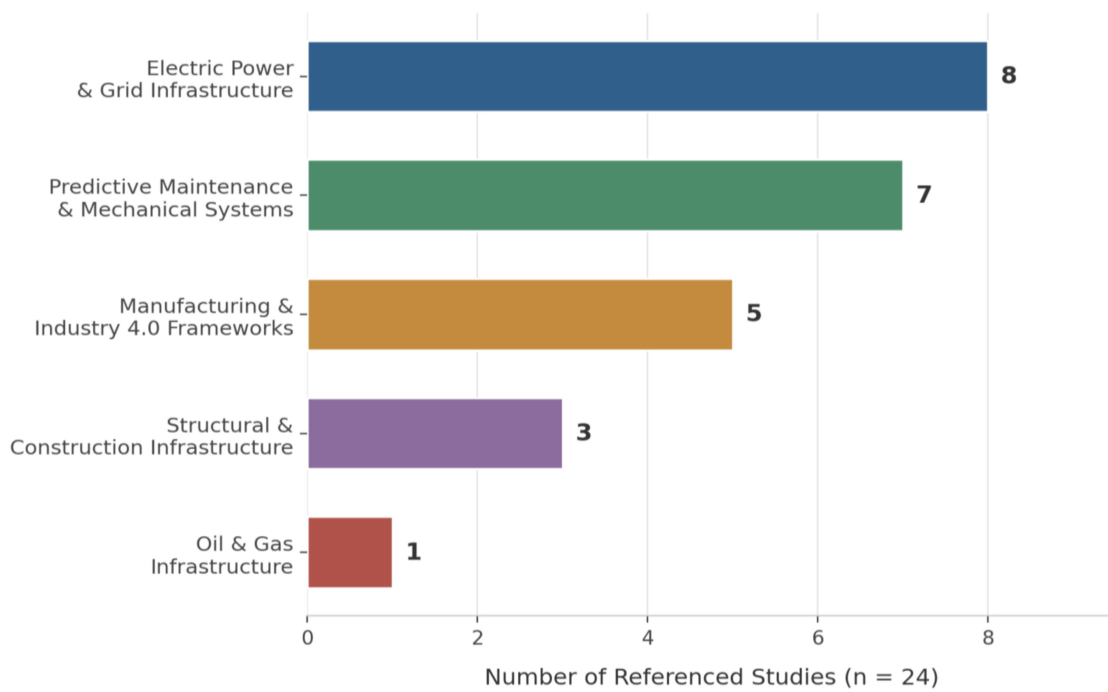

Figure 4. Domain Distribution of the Reviewed Literature (N = 24 Studies)

3.1 Distribution-Level Component Monitoring

Moutis and Alizadeh-Mousavi (2021) developed a digital twin of a distribution power transformer to generate medium-voltage-side waveforms of voltage, current, and active and reactive power, directly from low-voltage-side measurements, through a mathematical model of the transformer instead of dedicated medium-voltage instrumentation. It is important for predictive maintenance because it does not require the installation of medium-voltage measurement transformers on distribution feeders, and is claimed to achieve the same accuracy as instrument transformers without the associated cost, risk and network disruption. Similarly, Zhang et al. (2020) have introduced a digital-twin-based architecture for smart power distribution systems, which focuses on multi-layered integration between the physical power distribution assets and virtual models for situational awareness.

3.2 Distributed Energy Resources and Voltage Regulation

The work of Darbali-Zamora et al. (2021) also tackled a similar yet different problem: to optimize the output of distributed energy resources (DERs) to regulate the voltage of distribution feeders with limited telemetry. They used a platform they call the Programmable Distribution Resource Open Management Optimization System to implement their real-time digital twin, which was first tested in a power-hardware-in-the-loop simulation and then tested in the field with a 678-kW PV installation in Grafton, Massachusetts. The study's key contribution to the field of predictive maintenance is the ability to build a real-time digital twin that produces pseudo-measurements, which can replace in situ measurements in places where it would not be cost-effective to install a sensor. This allows condition monitoring to be expanded to a feeder without proportionate increases in the number of meters installed. A similar problem was tackled at the component level by Jain et al. (2020), who showed how to apply a digital twin model to a distributed PVs system for fault diagnosis, in which physics-based models of PV panel and inverter behavior are used with measured operating data to isolate the degradation and fault signatures that would be hard to tell apart from normal irradiance-induced output changes.

3.3 Smart Grid Platforms, Fault Prediction, and Security

On the systems level, Jiang et al. (2021) put forward a novel application architecture for digital twins in the smart grid, which extends the general five-dimensional reference model to system-wide monitoring and decision support – not for representations of one single asset. Before the proliferation of the five-dimensional digital twin model, the concept was already being adapted to the analysis of the power grid, as Zhou et al. (2019) showed in an earlier digital twin framework, specifically for power grid online analysis. The concept of a hybrid cyber-physical digital twin approach is proposed by Tzanis et al. (2020) for the prediction of faults prior to occurrence, specifically for smart grid applications, where a physical measurement is combined with a cyber-layer modeling. As the electric grid literature is reviewed, one security issue after another comes up, followed by a standardization one. Atalay and Angin (2020) suggested the concept of using a digital twin to test smart grid security and standardisation, pointing out that the same virtual replica can be utilised to test smart grid security and standardisation without risking the physical grid infrastructure, as it is used for predictive maintenance. Gehrmann and Gunnarsson (2020) discussed the closely related challenge of industrial automation and control system security and presented a digital-twin based security architecture for use in operational technology (OT) environments, which are the basis for both electric and gas utilities control systems. The electric grid applications described in this section and key methodological efforts are summarized in Table 3.

Table 3 **Selected Digital Twin Applications in Electric Grid Infrastructure**

Source	Asset / System Scope	Methodological Approach	Predictive Maintenance Contribution
Moutis & Alizadeh-Mousavi (2021)	Distribution power transformer	Mathematical low-to-medium-voltage transfer model	Medium-voltage fault identification without added instrumentation
Darbali-Zamora et al. (2021)	Distribution feeder with distributed energy resources	Real-time state estimation, hardware-in-the-loop and field validation	State-estimation pseudo-measurements in telemetry-sparse feeders
Jain et al. (2020)	Distributed photovoltaic systems	Physics-based fault-signature modeling	Isolation of degradation and fault signatures from irradiance noise
Jiang et al. (2021)	Smart grid (system-wide)	Extended five-dimensional application architecture	Grid-wide monitoring and decision support
Tzanis et al. (2020)	Smart grid fault conditions	Hybrid cyber-physical modeling	Anticipatory fault prediction
Atalay & Angin (2020)	Smart grid control systems	Digital twin security test-bed	Resilience testing without operational risk

4. Digital Twin Architectures for Gas Infrastructure

The volume of infrastructure, in particular gas and oil, is relatively small compared to the remainder of the reviewed corpus, with just one dedicated study that represents architectural principles that are directly applicable to the gas transmission and distribution network. Fielding a real-time operating data feed, AI-based analytics, and connection to the Internet of Things, Shen et al. (2021) proposed a digital-twin-based solution for production optimization and prediction for the design, operating, and control phases of the asset's lifecycle. The study positions the digital twin's main mission as its ability to integrate the information collected by the sensors and the experience gained by field personnel, thereby making the oil and gas asset systems more efficient than traditional supervisory control and data acquisition systems, where data collection and decision-making are considered two separate processes. While Shen et al. (2021) considered a physics-informed virtual model for upstream production rather than pipeline transmission or distribution, the general architecture of coupling continuous sensor telemetry with a physics-informed virtual model for diagnostic and optimization of the control system is similar to those of the transformer and feeder levels described in

Section 3 for electric infrastructure. The layered data, model and service structure was successfully validated in the electric distribution domain by Darbali-Zamora et al. (2021) and Moutis and Alizadeh-Mousavi (2021), and could be similarly applied in gas transmission and distribution, replacing the electric state-estimation models with pipeline hydraulic and compressor models. The architecture shown in Figure 5 is the general structure of what is referred to as a layered architecture that can be used for both electric and gas asset classes. The limited number of gas-specific digital twin studies identified in the reviewed period compared to the eight electric grid studies identified suggests that as of 2021, gas applications of digital twinning were less developed than electric grid applications, even if in the past, the former focused more on reservoir and production optimization than on transmission-asset condition monitoring (Shen et al., 2021).

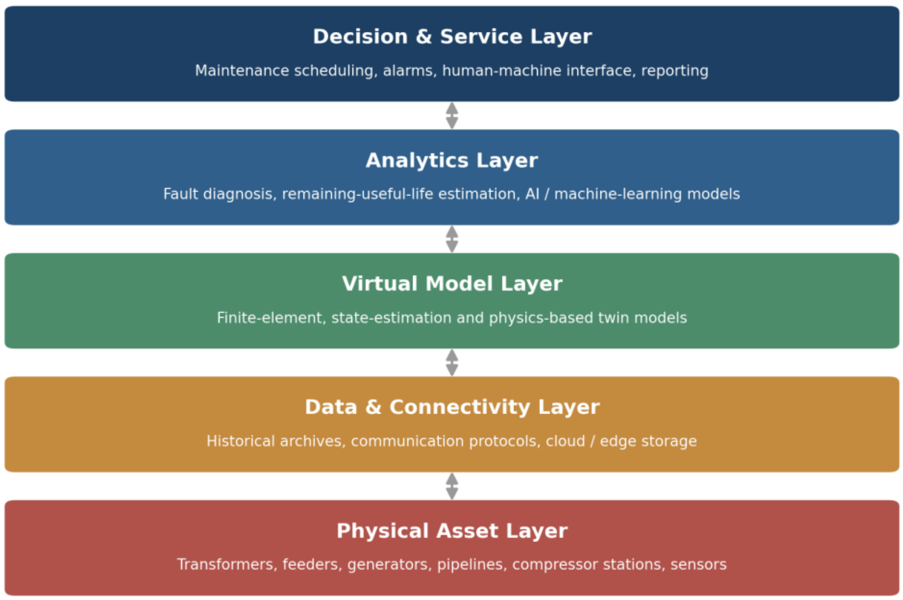

Figure 5. Generalized Layered Digital Twin Architecture for Electric and Gas Infrastructure

5. Predictive Maintenance Methodologies Enabled by Digital Twins

5.1 Physics-Based and Data Fusion Approaches

In both the electric and gas sectors, and also in the mechanical and manufacturing literature to which they refer, there are two complementary predictive maintenance methods using digital twins: physics-based modeling methods and data-driven methods and data fusion methods, most of the architectures reviewed including elements of both. The authors Liu et al. (2018) used data fusion in particular in the context of digital-twin based predictive maintenance and found that the diagnostic reliability of combining multiple sensor modalities, such as vibration, temperature, and electrical signature data from a virtual model, was superior to that of single-sensor approaches; similarly, the authors Falekas and Karlis (2021) observed that for state-of-the-art electrical machine condition monitoring, combining insulation testing, electrical signature analysis, and flux analysis is superior to relying on any single survey technique. The digital twin as a means for non-deterministic fatigue life prediction from in-situ diagnostic and prognostic data, has been proposed by Leser et al. (2020), because fatigue crack initiation and propagation is a highly uncertain phenomenon. The probabilistic approach is also important in the methods used for electric and gas infrastructure projects as the degradation of components such as transformers, cables and pipeline sections is also a random process and the estimate of remaining useful life based on a single value may be misleading for maintenance scheduling.

5.2 Domain Case Studies and Cross-Sector Transfer

Several studies reviewed–even those not in the electric and gas business per se–show predictive maintenance architectures that are readily applicable to the electric/gas business. Rajesh et al. (2019) created a digital twin of an automotive brake pad for predictive maintenance, using combined finite element and lumped parameter modeling followed by real-time monitoring of the brake pad wear, a structure similar to that of the transformer and feeder models discussed in Section 3. Savolainen and Urbani (2021) addressed maintenance optimization for a multi-unit system using digital twin simulation in the mining industry, which is a different perspective from the one applied to utilities (which tend to have many similar assets, such as transformers or compressor units). The concept model of a digital twin for integrated maintenance for crane operation was proposed by Szpytko and Salgado Duarte (2021), where the maintenance planning integrated with real-time operational data was highlighted, not diagnostics and scheduling. The concept of a predictive maintenance integrated decision-making approach with cooperative awareness based on the digital twin has been introduced by Mi et al. (2021), where the multiple twins related to the interconnected assets provide them information to aid system-level (as opposed to component-level) decision making, with a clear application to interconnected electric distribution networks and gas pipeline systems. The predictive maintenance methodologies found in these domain case studies are summarized in Table 4 according to technical approach.

Table 4 **Selected Digital Twin Implementations Supporting Predictive Maintenance Across Reviewed Domains**

Source	Domain / Asset	Technical Approach	Maintenance Outcome Emphasis
Falekas & Karlis (2021)	Electrical machines	Combined electrical, flux, and thermal condition monitoring	Unified predictive maintenance and control framework
Liu et al. (2018)	General rotating and mechanical assets	Multi-sensor data fusion	Improved diagnostic reliability
Leser et al. (2020)	Structural / mechanical components	Non-deterministic fatigue-life modeling	Probabilistic remaining-useful-life estimation
Rajesh et al. (2019)	Automotive brake pad	Finite-element and wear modeling	Component-level real-time wear tracking

Source	Domain / Asset	Technical Approach	Maintenance Outcome Emphasis
Savolainen & Urbani (2021)	Multi-unit mining system	Fleet-level simulation optimization	System-wide maintenance scheduling
Szpytko & Salgado Duarte (2021)	Crane operation	Integrated maintenance concept model	Combined operational and maintenance planning
Mi et al. (2021)	Interconnected industrial assets	Cooperative multi-twin awareness	System-level maintenance decision-making

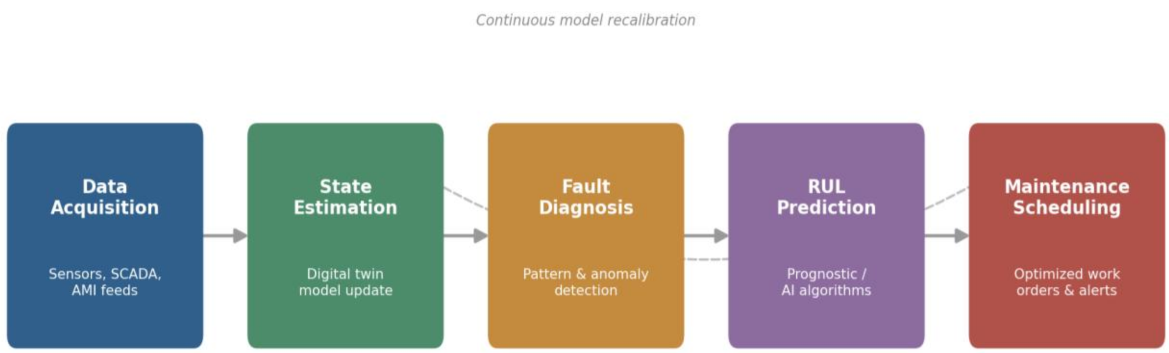

Figure 6. Predictive Maintenance Decision Workflow Supported by a Digital Twin

6. Enabling Technologies: Artificial Intelligence, Machine Learning, and Big Data

Rathore et al (2021) conducted a systematic literature survey on the various applications of AI, machine learning and big data in the context of digital twinning, and found that these are essential tools and not just nice-to-have for realizing the data dimension of the existing five dimensional reference model of digital twinning as the volume, velocity and variety of data generated by the modern sensing infrastructure is far more than can be handled by manual analysis or physics-based models in real time. Their review of volume 9 of IEEE access places the research field of artificial-intelligence-based digital twinning as a fast-growing, yet maturing field, as of 2021, and sees data quality, model interpretability, and computational cost to be current open challenges. Lu et al. (2020) presented a more comprehensive reference model for digital-twin-based smart manufacturing, providing an expression of the connotation of digital twin in Industry 4.0, and highlighting research challenges that may be common to the electric and gas applications outlined in Sections 3 and 4, such as the standardization of digital-twin data exchange formats and the integration of heterogeneous legacy equipment into uniform digital-twin architectures.

Lu et al. (2020) proposed a more comprehensive digital-twin-based smart manufacturing reference model, which captured the connotation of the digital twin in the context of Industry 4.0, and identified research questions that appeared in the reviewed electric and gas applications in Sections 3 and 4, such as digital-twin data exchange format standardization, as well as integrating heterogeneous legacy equipment into unified digital-twin architectures. Wagg et al. (2020) studied digital twins from a viewpoint of engineering dynamics, stating that there is a trade-off between fidelity and tractability of digital twins: high-fidelity models, such as full finite element representations, provide better diagnostics but can generally not be used at the rate required for real-time control, while reduced order or surrogate models sacrifice some fidelity and are therefore more tractable to real-time use. The inescapable conundrum of fidelity and tractability of digital twins is discussed explicitly in Falekas and Karlis (2021) in the context of black-box, grey-box, and white-box component models. Falekas and Karlis (2021) stated that artificial intelligence (AI) methods, such as neural networks and fuzzy cognitive maps, are being adopted more and more into the analytics layer of electrical machine digital twins (EMDTs) to differentiate fault indications which become indistinguishable from the variation of normal operating conditions when only rules-based or threshold-based methods are used. Table 6 categorizes the enabling-technology focus of the sources mentioned in this section, showing that the integration of AI and data processing is considered a cross-cutting issue and not limited to a specific field.

Table 6 **Enabling Technologies Emphasized Across the Reviewed Digital Twin Literature**

Source	Primary Enabling Technology	Reported Role in the Digital Twin Architecture
Rathore et al. (2021)	Artificial intelligence, machine learning, big data	Core data-dimension processing engine
Lu et al. (2020)	Reference-model standardization	Cross-vendor and cross-legacy-equipment integration
Wagg et al. (2020)	Reduced-order / surrogate modeling	Real-time computational tractability
Falekas & Karlis (2021)	Neural networks, fuzzy cognitive maps	Fault-indication classification in the analytics layer
Gehrmann & Gunnarsson (2020)	Security architecture design	Protection of the connection and data dimensions

7. Comparative Analysis and Cross-Domain Synthesis

When assessing the electric, gas, and nearby mechanical and structural applications discussed in Sections 3-6 it is clear that though there are similarities in architectural principles, there are differences regarding the maturity of implementation. All domains studied are focused on the five dimensional physical-virtual-data-connection-service structure as the preferred organizing structure, and all also highlight the need to integrate physics-based and data-based modelling rather than focusing on one or the other. The greater the maturity of implementation, the more apparent the differences in the different approaches, with electric distribution applications being at the stage of field-validated digital twin (as in Darbali-Zamora et al., 2021) and the sole gas-specific study reviewed, Shen et al. (2021), only at the level of an optimization model in development without a similarly documented field validation. Although not part of the electric and gas industry per se, structural and construction infrastructure provides another comparison.

Dang et al. (2020) developed a master digital model for suspension bridges, and Sofia et al. (2020) built upon the concept of digital twins and mobile mapping and machine learning in a case study of the Mohammed VI bridge in Morocco, as both case studies showed, large-scale, geographically distributed civil infrastructures, which also include electric transmission networks and gas pipelines, demands digital twin architectures that can represent spatially extensive assets rather than single discrete components. To further help mitigate this issue of accountability for information sharing, Lee et al. (2021) suggested linking blockchain with digital twins for supporting information sharing in construction projects, a governance mechanism that has the potential to be relevant to multi-stakeholder electric and gas infrastructure projects in which manufacturers, operators and regulators have to share information through the project life cycle without complete trust. Table 5 shows a comparative overview of the different studies, highlighting the coverage of the data at each lifecycle phase with service-phase monitoring being fully covered in all domains and design-phase and retire-phase being relatively underrepresented, mirroring the findings of Falekas and Karlis (2021).

***Table 5* Comparative Lifecycle-Phase Coverage Across Reviewed Digital Twin Studies**

Lifecycle Phase	Electric Grid Studies	Gas / Oil Studies	Mechanical / Structural Studies	Coverage Assessment
Design	Limited	Limited	Partial (finite-element inputs)	Least comprehensively addressed
Manufacturing	Minimal	Minimal	Partial	Rarely integrated with service-phase data
Service (operation & maintenance)	Comprehensive	Comprehensive	Comprehensive	Primary focus of nearly all reviewed studies
Retire	Minimal	Not addressed	Minimal	Identified as a research gap

8. Challenges and Future Directions

There are three recurring challenges in the literature reviewed. Second, with the deployment of digital twins for electric and gas infrastructure, there is a need for network connectivity to expand into operational technology environments traditionally shielded from external networks, where cybersecurity becomes a first order issue rather than an after-thought, as proposed by both Gehrmann and Gunnarsson (2020) and Atalay and Angin (2020) who suggest the digital twin can itself be used as a security testing mechanism. Secondly, standardization is not complete: Falekas and Karlis (2021) note that there is a coexistence between 3-, 5-, and 8-dimensional reference models, as well as different uses of the terms digital model, digital shadow, and digital twin for architecturally different models, which is identified as an active impediment for literature synthesis and by implication for industry-wide interoperability. Third, model fidelity and computational cost compete, as succinctly put by

Wagg et al. (2020): there is no reviewed study reporting a general solution to the trade-off other than domain-specific reduced-order modelling (ROM). Based on the reviewed literature, several future directions have been suggested, including expanding digital twin coverage to the design and retirement lifecycle phases, further integration of artificial intelligence (AI) into the analytics layer as recommended by Rathore et al. (2021); and increasing gas and oil transmission-related digital twin research to be more comparable to the relative maturity of electric distribution-related digital twin research by 2021. In addition, the cooperative multi-twin architecture proposed by Mi et al. (2021) indicates that system-level, not just single-asset, approaches to digital twin architectures are a promising direction for both electric distribution networks and gas transmission networks, due to the intertwined nature of failure propagation between the two.

9. Conclusion

By the end of the reviewed timeline, a synthesis of the twenty-four studies revealed a consistent conceptual framework of five dimensions for digital twin architectures of predictive maintenance for electric and gas infrastructure, but with varying levels of maturity in the implementation in each of the sectors. Among the analysed collection, electric distribution applications are among the most developed, as shown by Darbali-Zamora et al. (2021), in the analysed case of 678-kilowatt photovoltaic generation, and Moutis and Alizadeh-Mousavi (2021), with their transformer-monitoring architecture; gas and oil infrastructure applications, represented mainly by Shen et al. (2021), are less mature. The key remaining issues cited in the literature are cybersecurity, standardization, and the fidelity-computation trade-off. The gap of lifecycle-integration in the design and retirement phases, as well as the cooperative system-level twin architectures, are the most relevant future research and industrial development directions in both sectors.

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