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Taxonomy of digital twins for power grids

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A R T I C L E   I N F O

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A B S T R A C T

Digital twins (DTs) are increasingly adopted in the energy sector, yet existing conceptual frameworks and maturity models remain largely generic, limiting their usefulness for power grid applications with stringent requirements for resilience, security, and lifecycle integration. This paper proposes an upgraded taxonomy of DTs tailored to power grid systems, extending earlier generic frameworks and aligning them with the ISO/IEC30186:2025 maturity model. The taxonomy introduces domain-specific dimensions, including cyber-physical security integration, intelligence level, and multi-layered data architectures, while ensuring compatibility with internationally standardized maturity aspects. A comprehensive literature analysis and co-occurrence study underpin the revisions, ensuring both methodological rigor and relevance to current research and practice.

The taxonomy's analytical and practical value is demonstrated through its application to three real-world DT use cases: KOEN (generation-focused), Elvia (distribution-focused), and Bentley OpenUtilities (lifecycle-integrated). Comparative benchmarking across these cases highlights both commonalities and context-dependent maturity profiles, confirming that DT maturity is not absolute but shaped by organizational objectives, technical architectures, and sectoral priorities. The taxonomy also enables scenario-based reasoning and role-specific insights, supporting cybersecurity analysis, operational decision-making, and business risk evaluation. By combining academic rigor, sector-specific focus, and alignment with international standards, the proposed taxonomy offers a replicable framework for assessing and improving DT maturity in power grids. An interactive tool, openly available on GitHub, further supports its practical application by enabling benchmarking, visualization, and recommendations. In this way, the work contributes both to scholarly discourse on DT conceptualization and to the practical adoption of maturity frameworks by utilities, regulators, and technology providers.

1. Introduction

The evolution of electrical power systems toward increased complexity, decentralization, and digitalization has brought about unprecedented challenges in grid planning, operation, and maintenance. In response to these challenges, Digital Twins (DTs) have emerged as a transformative solution, offering dynamic, data-driven virtual models that mirror the real-time behavior and state of physical systems [1]. A DT is broadly understood as a virtual representation of a physical asset or system that remains synchronized with it through sensor data and computational models, enabling predictive, diagnostic, and prescriptive analytics across the grid lifecycle [2]. In power grids, DTs replicate subsystems such as substations, transformers, or entire network topologies, capturing their real-time behavior and facilitating continuous monitoring, simulation, and optimization. Their implementation in grid environments has shown measurable impact in enabling condition-based maintenance, improving asset utilization, enhancing resiliency, and informing strategic planning [3,4]. These functionalities make them an essential enabling technology for modernizing the grid in line with smart infrastructure and energy transition goals.

Challenge. Despite the growing adoption of DTs across the energy sector, there remains a notable lack of conceptual clarity and methodological consistency in how they are implemented, evaluated, and aligned with operational, regulatory, and cybersecurity requirements. In particular, the heterogeneity of DT architectures, purposes, and deployment contexts in the power grid domain makes it difficult to assess their readiness, interoperability, and value contribution across diverse lifecycle stages and system hierarchies. Thus, the field remains fragmented, with varying definitions and inconsistent architectural implementations. Researchers and practitioners tend to focus on isolated features such as control algorithms, machine learning models, or sensor integration, while overlooking the broader architectural, lifecycle, and user-oriented aspects necessary for interoperable and trustworthy deployment.

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Necessity. Given the strategic role of power grids in national infrastructure and the high stakes associated with their operation, there is a pressing need for frameworks that help characterize, evaluate, and guide the development of DTs in a consistent and comprehensive manner. Such frameworks must account not only for data aspects, modeling techniques, and domain-specific applications, but also for human interaction, lifecycle integration, intelligence advancement, and regulatory alignment.

Gap. While several taxonomies have been proposed to structure the broad concept of DTs in manufacturing, healthcare, and aerospace [5,6], these frameworks often fall short in addressing the distinctive challenges of power grids, such as: integration of legacy systems, distributed generation, multi-layered governance structures, stringent cybersecurity needs, and the evolving role of regulatory compliance and market operations in digital transformation (Y. [7]. Thus, they remain generic or domain-agnostic. Moreover, prior work rarely includes key operational dimensions, such as synchronization frequency, interface types, cybersecurity functions, or stakeholder roles [8,9]. These omissions limit the utility of such taxonomies in real-world implementation scenarios where coordination across technical, managerial, and regulatory actors is essential. There is, therefore, a clear gap in the literature for a structured, power-grid-specific taxonomy that also incorporates human–computer interaction considerations.

Direction. This paper addresses this gap *by proposing an upgraded, domain-specific taxonomy of DTs for power grid systems* that explicitly captures both the technical and human-centered dimensions of DT design and evaluation. The taxonomy is based on a comprehensive synthesis of existing literature, a bibliometric co-occurrence analysis, and insights from emerging standards. It builds on current foundational taxonomies, particularly the one proposed by van der Valk et al., [10], extending the classification along ten core dimensions relevant to grid operations, architecture, lifecycle, and cyber-physical security. These dimensions include not only traditional elements like data flow and model granularity, but also advanced concerns such as intelligence level, cybersecurity integration, and the position of the DT across the asset lifecycle.

In addition to presenting the taxonomy, *we also demonstrate how the newly devised taxonomy can be operationalized to assess maturity and improve real-world DT implementations.* To this end, *we developed an interactive software tool, openly available on GitHub,* which implements the taxonomy and generates both overall and dimension-specific maturity scores. The tool provides visual analytics, such as radar plots and heat maps, enabling comparative benchmarking across multiple DTs and offering actionable recommendations. Through simulations and real-world use case mappings of three systems (Korea South-East Power Co. (KOEN) DT, Elvia's low-voltage DT in Norway, and Bentley's OpenUtilities suite), we show how the taxonomy reveals actionable insights, identifies gaps, evaluates maturity, and generates role-specific recommendations for security, business, architecture, and compliance experts. By doing so, this work contributes to the ongoing effort to develop comprehensive methodologies for DT maturity assessment and offers practical tools for benchmarking, implementation planning, and decision support in power grid contexts.

The remainder of this paper is organized as follows. Section 2 provides the theoretical background necessary for understanding the key concepts and methodological choices underlying this work. Section 3 presents a comprehensive analysis of the state of the art, identifying the most recent and relevant developments in the energy sector that inform the design of a domain-specific taxonomy. Building on this foundation, Section 4 introduces the proposed taxonomy for DTs in power grid systems, detailing its dimensions in light of both the preceding analysis and the reference taxonomy of van der Valk et al. [10]. Section 5 aligns the taxonomy with the [11] maturity aspects and applies it to three real-world use cases to demonstrate its applicability and enable comparative benchmarking. Section 6 discusses the broader implications of the findings, outlines the contributions and limitations of the study, and reflects on practical and research perspectives. Finally, Section 7 concludes with key insights and provides directions for future work.

2. Background

This section provides a definition and discussion of DTs and their conceptualization, followed by an overview of existing conceptual frameworks and taxonomies, with particular emphasis on those relevant to the energy sector.

2.1. Digital twins

At a technical level, DTs are structured in multi-layered architectures that include physical, data, model, simulation, and application layers [12]. These layers collectively enable the integration of field data with advanced simulation and decision-support tools. Moreover, DTs exhibit varying levels of fidelity, from static digital models and real-time shadows to fully interactive DTs with bidirectional control capabilities, depending on the degree of connectivity, model accuracy, and computational capability [13,14]. Hence, their implementation in power grids is underpinned by a convergence of enabling technologies such as artificial intelligence (AI), edge/cloud computing, data analytics, and advanced visualization platforms. These technologies support the core DT functionalities, facilitating a shift from reactive to proactive and autonomous grid operations.

Recent research demonstrates the growing role of DTs in supporting decentralized grid management, integrating renewable generation, and ensuring cybersecurity. Particularly, DTs are being used to simulate and evaluate cyber-physical threats, providing a safe testbed for intrusion detection, anomaly classification, and vulnerability assessment [15,16]. However, the integration of DTs into real-world power systems remains complex, constrained by issues like interoperability with legacy infrastructure, data silos, and limited standardization. Moreover, as distributed energy resources (DERs) and prosumers proliferate, the grid's architecture is evolving from a centralized "hub-and-spoke" model to a more distributed and adaptive configuration. In such environments, DTs must not only reflect operational dynamics, but also support lifecycle governance. To do that, it is critical to understand and document the variety of ways in which DTs are modeled, categorized, and assessed in practice. This has led to a proliferation of conceptual frameworks and taxonomies, each attempting to structure the field by emphasizing different dimensions such as architecture, data integration, intelligence, lifecycle coverage, or maturity. These frameworks are particularly important because they provide the analytical scaffolding through which DTs can be systematically compared, benchmarked, and evaluated across domains. The following subsection therefore reviews key conceptual models and taxonomies, highlighting both their general contributions and their limitations, and setting the stage for the domain-specific framework proposed later in this paper.

2.2. Conceptual frameworks for digital twins

In the broader DT literature, conceptual frameworks and taxonomies have played an important role in bringing clarity to an otherwise heterogeneous field. General models such as those of [17] and [6] emphasize DT architectures and key enabling technologies, whereas others, such as [18], focus on maturity models and staged progressions of DT implementation across infrastructures. Similarly, (Y. [7] provides maturity-oriented and evaluative models that highlight capabilities and performance indicators, while [19] review key technologies underpinning intelligent digital grids from a conceptual perspective. However, as Table 1 illustrates, many of these frameworks are either sector-independent or tailored to manufacturing and IoT contexts, with limited attention to energy-specific challenges. Moreover, cybersecurity and resilience, although central in critical infrastructures, are often treated only implicitly or as secondary concerns, leaving conceptual

Table 1
Literature-based comparative analysis of DT-oriented frameworks and taxonomies.

Framework	Taxonomy	Granularity	Lifecycle Integration	Cybersecurity Coverage	Power Grid Specificity
This paper	√ Yes	√ High	√ Yes	√ Yes	√ Yes
[10]	√ Yes	− Medium	− Partially	× No	× No
[17]	× No	√ High	− Implicit	× No	× No
[18]	− Partially	√ High	√ Yes	− Moderate	− Adaptable
[20]	× No	√ High	√ Yes	× No	√ Yes
[6]	× No	− Medium	× No	× No	× No
(Z. [21]	× No	√ High	√ Yes	− Indirect	− Adaptable
(ISO/IEC 30186, 2025)	− Partially	√ High	√ Yes	− Moderate	− Adaptable
(Y. [7]	− Partially	√ High	√ Yes	√ Yes	× No
[19]	× No	√ High	√ Yes	× No	√ Yes

gaps that must be addressed in energy-focused taxonomies.

Within the energy and power grid domain, efforts to develop DT frameworks remain comparatively scarce and fragmented. For instance, Brosinsky et al. [14] and Bragatto et al. [13] present DT concepts for energy management and active distribution networks, respectively, while [19] propose a high-level structure for digital power grids. Yet, as Table 1 shows, these studies rarely combine lifecycle integration, cybersecurity, and grid-specific requirements into a coherent taxonomy. Standardized models such as the Smart Grid Architecture Model (SGAM) [20] and the [11] framework (ISO/IEC 30186, 2025) provide useful reference points for layered architectures and maturity assessment, but they remain either too broad or too generic for practical evaluation of power grid DTs. This points to a need for domain-specific conceptualizations that capture not only technical fidelity and synchronization, but also lifecycle governance, cyber-physical security, and cross-domain integration. Addressing these limitations is the motivation for the revised taxonomy proposed in this paper, which builds on existing models, while tailoring its dimensions to the unique operational and strategic requirements of the energy sector.

2.3. Van der Valk's taxonomy of digital twins

Van der Valk et al., [10] developed a multi-dimensional taxonomy of DTs through a comprehensive literature review of 233 scholarly sources. Their taxonomy provides a classification framework that organizes the defining features and properties of DTs across diverse application domains, as shown in Fig. 1. Unlike prior efforts that were tied to a specific sector (manufacturing or healthcare), this taxonomy adopts a domain-independent perspective, enabling the comparison and analysis of DT implementations based on consistent dimensions. It follows the methodology of Nickerson et al. [22], and is underpinned by a *meta*-characteristic: *the central, distinguishing features and properties of Digital Twins*. This makes the taxonomy especially suited for identifying commonalities and differences in DT architectures and their operational models, regardless of their industry-specific uses. The taxonomy includes eight dimensions, some mutually exclusive (to which only one characteristic applies), while others are non-exclusive (multiple characteristics may apply):

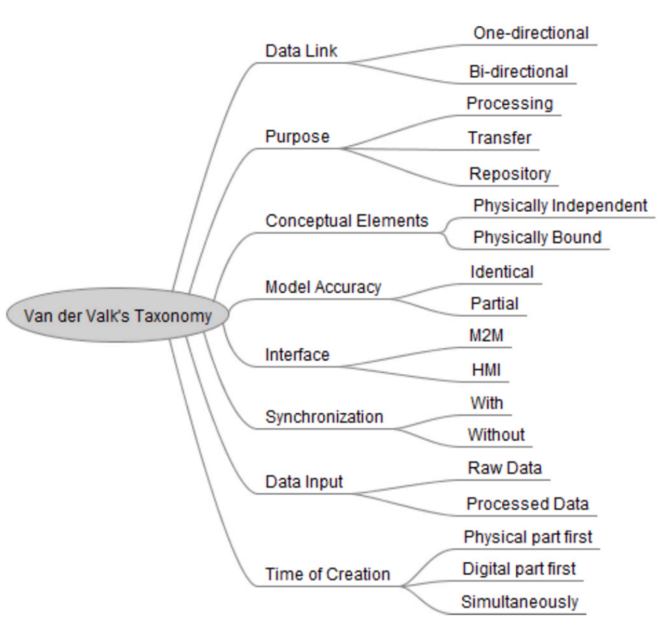


Fig. 1. Van der Valk's Taxonomy of Digital Twins.

The *Data Link* informs whether the communication between physical and digital entities is one-directional or bi-directional. *Purpose* shows whether the DT processes, transfers, or stores data (can be any combination). *Conceptual Elements* denotes if the DT is physically bound or independent of the physical system. *Model Accuracy* means whether the digital model is identical to the physical system or it is only a partial representation of it. The *Interface* describes the support for machine-to-machine (M2M) or human–machine (HMI) interaction. *Synchronization* shows whether the DT is updated synchronously or not. *Data Input* contains information on whether the DT uses raw, processed, or both types of data. Finally, the *Time of Creation* informs whether the DT is created before, after, or simultaneously with its physical counterpart. These dimensions allow for granular classification of DTs, helping researchers and practitioners understand which architectural choices have been made, and to what end. The importance of this taxonomy lies in that it supports a multi-dimensional view, highlighting that DTs are not monolithic systems, but complex entities whose properties span across data handling, fidelity, interfacing, and temporal alignment.

While Van der Valk's taxonomy is broad and well-structured, applying it directly to power grid systems, particularly those involving cyber-physical infrastructures like power grids or Digital Substations, requires contextual refinement for several reasons:

1. Interoperability requirements: Power grids must operate across multiple layers (business, function, information, communication, component), as defined in standard models like SGAM[20]for the context of smart grids and RAMI 4.0[23] for the general Industry 4.0 context. Thus, DTs for grids require layer-aware classification, which is not fully captured in the current taxonomy.
2. Lifecycle integration: Van der Valk's taxonomy only implicitly addresses the lifecycle alignment of security, governance, and regulatory compliance, which are crucial for critical infrastructures. Power grid DTs must integrate cybersecurity and compliance from early design to retirement.
3. Human-in-the-loop dynamics: Power systems demand shared governance, involving operational teams, IT personnel, and regulatory stakeholders. While the "interface" dimension accounts for interaction types, it does not fully capture collaborative decision-making workflows. This is especially critical nowadays, with the advancement of generative AI and multi-agent systems.
4. Threat modeling and resilience: Power grids are high-value targets for cyber-physical threats. DTs in this domain must often embed

resilience planning, attack simulation, and adaptive threat response, which the taxonomy does not explicitly cover.

5. Regulatory and geopolitical diversity: Unlike the manufacturing domain where many DT applications originate, power systems are deeply shaped by national regulations, public accountability, and cross-border energy trading. Therefore, taxonomy dimensions need to account for policy alignment and trust frameworks.

To ensure that a revised taxonomy is both comprehensive and aligned with current developments, it is necessary to conduct a systematic and wide-ranging literature analysis. This is presented next in the paper. The comprehensive literature review, complemented by a co-occurrence analysis of key terms, serves two purposes: first, it provides an evidence-based overview of how the field has evolved in both scope and focus, allowing us to identify concepts and dimensions absent from Van der Valk's original taxonomy. Second, the co-occurrence analysis revealed the relationships between recurring terms and themes, highlighting clusters of research activity and areas of conceptual convergence. This creates a robust empirical basis for revising and extending the taxonomy, ensuring that the upgraded framework is not only theoretically consistent, but also grounded in the actual state of the art.

3. Comprehensive analysis of the state of the art

3.1. Research methodology

The construction of the visual and analytical map of research on DT technology for power grids is grounded in a multi-phase process that combines semantic bibliometric analysis with systematic screening and thematic synthesis under a general PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology [24]. This approach enables both a macro-level understanding of the field's intellectual structure and a micro-level extraction of actionable insights.

For building the search string, database querying, and visualization, we use VOSviewer,[1] a specialized software tool that uses advanced text mining and natural language processing (NLP) techniques to generate a co-occurrence network[25]. VOSviewer was selected due to its methodological alignment with the research objective of uncovering thematic structures in the DT literature, but also because it offers rigorous approach for extraction and visualization, which is essential for identifying dominant research clusters and semantic patterns[25]. Other tools, like BibExcel are primarily designed for data preprocessing and require external tools for network visualization [26]. Similarly, CitNetExplorer, specializes in citation network exploration but lacks integrated term co-occurrence features[27]. While CiteSpace[28]and Bibliometrix/Biblioshiny [29] do offer complementary functionalities (such as burst detection or thematic evolution), they are less optimized for the specific task of generating detailed co-occurrence maps based on textual metadata. VOSviewer provides a cohesive environment for both data processing and interactive visual analysis. In the visualization map produced by VOSviewer, nodes represent terms and edges represent their frequency of co-mention within the same documents. Given the focus on mapping conceptual proximities and identifying latent research gaps, the clustering algorithm and distance-based layout of VOSviewer proved as the most suitable choice for supporting the semantic exploration required in this work. In the visualization map produced by VOSviewer, nodes represent terms and edges represent their frequency of co-mention within the same documents.

To enhance the precision and relevance of the analysis, the semantic mapping was refined, filtering the dataset according to a set of exclusion criteria (like removing duplicated or low-quality records, excluding papers that do not offer technical depth or direct relevance to DT applications in power systems). In addition, the scope was limited to peer-reviewed journal articles and high-quality conference proceedings. This screening narrows the focus to a smaller subset of documents that are closely aligned with the identified clusters and research questions. This curated set forms the basis for deeper qualitative and quantitative investigation. Hence, the final phase represents a deep-dive analysis of the refined set of papers, where each selected document is reviewed to extract specific information across dimensions such as: modelling approaches, application domains, technological enablers, validation methods, and implementation technology. The outcome of this approach is not only a clearer view of how DTs are shaping the future of power grids, but also a set of targeted recommendations for advancing research, development, and deployment. Fig. 2 summarizes the overall process of the PRISMA methodology followed in the literature review, showing the number of records excluded in each phase, until narrowing it down to a very focused curated set of the most relevant works for our purpose.

3.2. Identification Phase: Analysis and visualization of the research literature

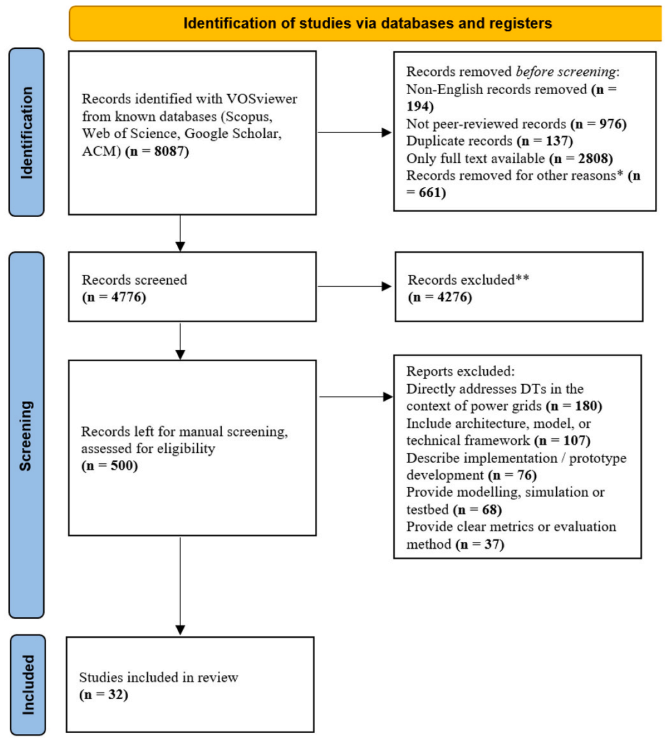
The systematic screening process is guided by a combination of semantic analysis and bibliometric filtering, carried out using the VOSviewer tool. The first step involves obtaining a suitable dataset of publications for constructing and analyzing the co-occurrence of scientific terms within the field of interest in a given period. To begin, a targeted search query is constructed to reflect the scope of interest, focusing on the intersection of DTs and power grids, as well as the architectural (system) considerations of their application in the domain. This query is run across major scientific publication databases (Scopus, Web of Science, Google Scholar, ACM) through the VOSviewer interface and data import features. To construct a robust dataset, we use the following search string:

`“Digital twin” AND (“Smart Grid” OR “Power Grid” OR “energy grid”) AND “architecture”`

Applying the term “architecture” reflects the specific focus on the structural, systemic, and functional arrangements of DTs, ensuring that the retrieved works extend beyond generic descriptions of DT applications and include explicit consideration of system architecture, data flows, and integration frameworks. The scope of the search was limited to publications from 2020 to 2025, ensuring the inclusion of only the most recent and relevant research. This initial query yields a corpus of 8077 documents, which then underwent further refinement based on semantic criteria and predefined exclusion filters to enhance dataset quality and focus. The criteria and the outcomes of this initial screening are shown in the *Identification* step in Fig. 2. After applying the exclusion criteria, 3301 documents were removed, leaving 4776 for the *Screening* step and for the term co-occurrence analysis. For this analysis, we applied a binary counting method, where only the presence or absence of a term in a document is considered, regardless of how frequently it appears. A minimum occurrence threshold is also set to filter out low-frequency noise; in our case, terms must appear in at least 10 documents to be included. Out of a total of 89,010 terms, 2273 met this threshold. To further refine the semantic map, a relevance score is calculated, selecting the top 60 % of terms based on their distribution and connectivity. This results in a final visualization dataset comprising 887 terms, forming 95,711 links with a total link strength of 201,280, which is a strong indication of the semantic richness and interconnectedness of the research field. This method enables us to identify core thematic clusters, uncover emerging research areas, and establish a quantitative foundation for further in-depth analysis. The final visualization represents a scientific co-occurrence network visualization depicting four major clusters, each corresponding to a different research focus. This is shown in Fig. 3.

In addition to revealing keyword clusters, the figure shows how research topics group and relate within the DT ecosystem in energy

[1] https://www.vosviewer.com/.



* Other reasons = Irrelevant based on title and abstract screening + No technical depth + Not focused on power systems
**All records were excluded as a result of human-made decision, leaving the top 500 records for manual screening

Fig. 2. PRISMA flow diagram of the literature review process.

systems. Each node represents a keyword, whereas node size reflects keyword frequency. Edge thickness indicates co-occurrence strength, the colors separate the clusters (themes), and the proximity of objects reflects their semantic relatedness.

The red cluster in the co-occurrence network reflects a strong focus on enterprise strategy, management, and evaluation, particularly in the context of large-scale DT adoption. Central keywords suggest institutional and strategic deployment of DT technologies, with a notable geographic emphasis on China, where there is a significant concentration of research and practical implementation in policy-driven and state-supported environments. The themes emerging from this cluster highlight the role of DTs in enhancing operational efficiency, enabling predictive and preventive maintenance, and supporting lean management practices. Organizations are increasingly using DTs not only as technical tools but as integral components of business intelligence and asset management. Other terms like indicator, evaluation, and digital economy point to a rising demand for quantifiable performance metrics and structured cost-benefit analysis to justify and optimize DT investments. Moreover, the presence of big data and information technology underscores the convergence of DTs with enterprise-level IT systems, facilitating data-driven decision-making at both the operational and strategic levels.

The green cluster represents a concentrated body of research on cybersecurity, detection, and measurement within the context of DT technology for power grids. The central themes here reflect the importance of DTs as tools for identifying and mitigating cyber-physical threats. Techniques such as anomaly detection and defense against false data injection attacks are prominent, supported by the use of advanced machine learning (ML) algorithms including neural networks and feature extraction methods. Feature extraction directly impacts DT fidelity, as it determines how well the virtual model reflects the operational state of the physical grid. In DT implementations aimed at real-time grid health monitoring or cyber-attack detection, feature extraction pipelines are embedded in the data ingestion layer, allowing the DT to remain responsive and predictive without being overloaded by raw data volume. Hence, a defining feature of the green cluster is its emphasis on real-time monitoring and analysis. Technologies like Phasor Measurement Units (PMUs) play a critical role, enabling the collection of high-frequency data necessary for fast and accurate detection of grid anomalies.

In addition to the technical terms, the appearance of *IEEE* in the green cluster as a frequently associated term reflects ongoing efforts to align DT implementations with recognized industry standards, ensuring interoperability and reliability. This alignment is particularly important in power grid contexts, where frameworks like [87] (for industrial cybersecurity), [88] (for communication with DERs), and IEC 61850 (for substation automation protocols) offer critical guidance for structuring secure and interoperable systems. Similarly, standards like [89] govern DER interconnection, while the emerging [90] and ISO/IEC 30,186 frameworks address the formal representation and maturity evaluation of DTs. Their integration into DT architectures enhances not only technical compatibility across systems, but also regulatory compliance and operational resilience.

The blue cluster represents the technical and engineering core of DT research in power grids, emphasizing areas such as control systems, optimization, and grid dynamics. The dominant keywords here reflect a deep engagement with the mechanisms that maintain grid stability and performance. This cluster is particularly focused on simulating and managing the behavior of dynamic components in the grid, including wind power, energy storage systems, and unbalanced or low-inertia power systems. At the core is the use of DTs as real-time simulation and actuation tools. DT-technology is leveraged to model the interactions between converters, storage devices, and fluctuating energy sources, enabling predictive control and fine-tuning of grid parameters such as voltage and frequency. The attention to components like harmonic distortion, VSCs (voltage source converters), and power output showcases the precision with which DTs are being applied to tackle emerging engineering challenges in decentralized and renewable-heavy

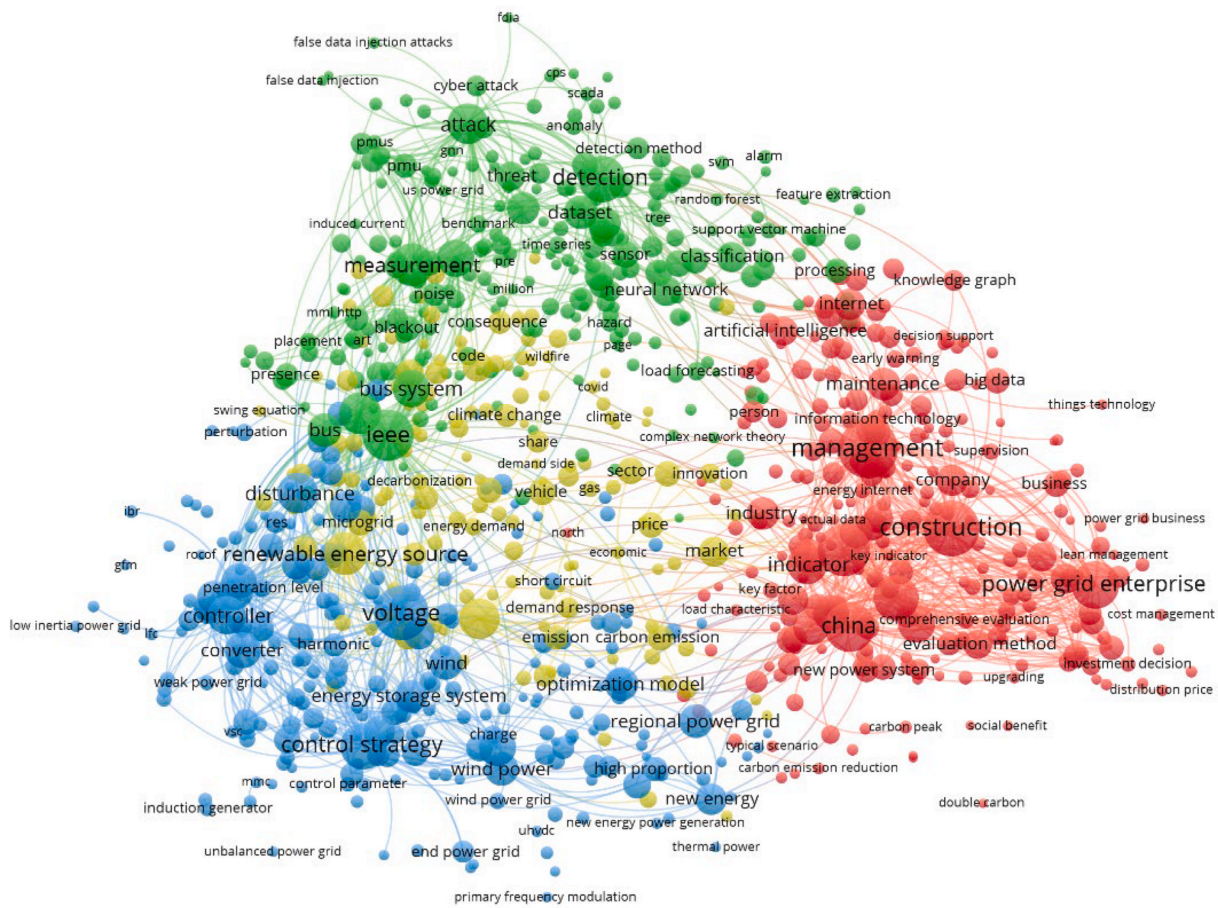


Fig. 3. Co-occurrence network visualization of the research literature.

grid environments. This reinforces the concept of DTs as active participants in power system control loops, rather than static digital replicas.

Finally, **the yellow cluster** centers on the role of DT technology in advancing sustainability, emission reduction, and the global energy transition. The prominent themes in the cluster highlight a research focus that joins environmental goals with economic modeling. This cluster captures DTs' application as strategic tools to model, simulate, and optimize low-carbon energy systems. In this context, DTs are used for forecasting emissions, analyzing renewable energy penetration, and exploring climate scenarios, enabling energy planners and policymakers to make informed, data-driven decisions. Terms like *optimization model, price,* and *energy demand* reflect a growing integration of energy economics into the design of DT systems, supporting evaluations of market responses, cost-benefit dynamics, and investment risks associated with clean energy adoption. The presence of demand response strategies suggests a move toward adaptive grid behavior, where DTs enable simulation of consumer behavior and flexible load management under varying environmental and market conditions.

3.2.1. *Cross-cluster integration*

The cross-cluster integration themes in the DT research landscape reveal the increasing interdisciplinarity of the field, where technical, strategic, and environmental aspects converge to create more holistic and responsive energy systems. These thematic intersections highlight the synergistic roles of DTs across different domains and point toward the emergence of comprehensive, multi-functional platforms for grid innovation.

The intersection between the red and green clusters (enterprise management and cybersecurity) illustrates the integration of organizational oversight with real-time threat monitoring. This reflects how DTs are being embedded into enterprise systems not just for asset management and operational analytics, but also for incorporating cybersecurity dashboards, enabling companies to align performance management with risk detection and mitigation strategies. The connection between the green and blue clusters (security and control systems) demonstrates the convergence of intrusion detection mechanisms with dynamic control architectures. Here, DTs serve as both observers and actors, detecting anomalies and simultaneously recalibrating control strategies in response to detected threats. This enables resilient grid operations, particularly in the face of sophisticated cyber-physical attacks. The bridge between the blue and yellow clusters (control and sustainability) shows how DTs are central to managing low-carbon, distributed energy systems. In this integrated view, DTs are not only stabilizing systems through real-time control but also optimizing performance against environmental objectives like emissions reduction and renewable integration. This positions DTs as key enablers of climate-aligned grid operations. Finally, the link between the yellow and red clusters (sustainability and enterprise strategy) demonstrates the growing importance of carbon accounting, ESG (Environmental, Social, and Governance) metrics, and sustainability indicators in corporate energy strategies. DTs help organizations simulate, track, and report environmental performance, making them essential tools for strategic investment, regulatory compliance, and stakeholder engagement.

3.2.2. *Discussion and research opportunities*

The insights derived from these analyses offer a high-level understanding of where DT research in the energy sector is currently concentrated, as well as where it may evolve in the near future. One notable pattern is China's dominance in the red cluster. This may reflect a substantial national-scale deployment and research investments in DT technologies by Chinese power enterprises, highlighting China as both a prominent market player and a research hub. Another key insight is the multidisciplinary expansion of the field. While the blue cluster reflects DT's engineering roots in control systems and dynamic modeling, the yellow cluster incorporates economic modeling, sustainability, and policy evaluation, and the red cluster anchors DTs in corporate strategy and transformation. This broad spread across clusters illustrates how DTs have evolved from niche simulation tools into complex socio-technical systems, enabling decision-making at both operational and strategic levels. The green cluster's focus indicates that cybersecurity has emerged as a standalone research pillar within DT applications. With its dedicated cluster centered around anomaly detection, classification, and threat mitigation, cybersecurity is treated not as an auxiliary feature but as an integral function of DT ecosystems, particularly for critical infrastructure protection. The role of AI and Internet of Things (IoT) is also prominent, reflecting the infusion of AI and ML into DT architectures.

However, the analysis also reveals several critical research gaps and future opportunities. Concepts like **human-in-the-loop** systems, which integrate human decision-makers into DT feedback loops, are noticeably underrepresented. Similarly, there is a lack of research explicitly addressing **interoperability**, which is vital for integrating DTs with legacy infrastructure and across vendor ecosystems. Additionally, **ethical and regulatory considerations**, such as data privacy, accountability in autonomous decisions, and algorithmic transparency, are largely missing from current discussions. Although *IEEE* appears as a keyword, there is little depth in the exploration of **standardization frameworks**, indicating a need for more structured guidelines to support scalable and secure deployments. Finally, there is an absence of emphasis on **cross-border and regional power trading scenarios**, a crucial consideration as grids become increasingly interconnected and decarbonization efforts demand transnational coordination. These gaps present rich opportunities for future exploration, innovation, and policy development in the rapidly expanding field of DT technology for power systems.

3.3. Screening phase: In-depth analysis of the most relevant research approaches

The co-occurrence analysis with VOSviewer provided valuable insight into the structure of the research field. In order to enable a granular assessment of methodological rigor, practical implementation, and technical contributions, a second phase of analysis was carried out to identify and examine the most relevant and impactful papers in greater depth. To move from broad mapping to focused insight, the initial dataset underwent screening by progressive refinement using another set of exclusion criteria, as shown in the *Screening* step in Fig. 2. The aim was to isolate studies that offered substantive and technically detailed contributions to the field of DTs in power grid systems. Thus, from the initial 4776 papers, the top 500 most relevant documents were selected for manual screening. Through this filtering process, we arrived at a final curated set of 32 papers that met all or most of the following inclusion criteria:

- The study must directly address DT applications within the context of power grids;
- Papers must include a proposed architecture, model, or technical framework;
- They must go beyond theory, describing system-level implementation or prototype development;
- Detailed modeling approaches, simulation environments, or testbeds must be provided; and
- Clear metrics or evaluation methods must be reported.

The papers were assessed holistically, and inclusion was based on whether they satisfied a critical mass of these criteria, rather than any single dimension. Each of the 32 selected papers was analyzed using a standardized data extraction protocol designed to align with the clusters and density trends identified in the VOSviewer analysis. The extraction focused on five analytical dimensions:

- Study focus, which determines the general area within the power grid research the specific approach falls into. This helps position the paper in some of the previously defined clusters.
- Implementation type, which classifies the modeling paradigm employed by each study as physics-based, data-driven, or hybrid, and documented specific modeling techniques and computational frameworks.
- Grid application area, which maps the paper to one or more grid domains, including generation, transmission, distribution, micro-grids, and DER integration, identifying specific use cases like state estimation, stability analysis, or renewable coordination.
- Key technology, which records the technologies employed, such as IoT sensors, SCADA systems, AI/ML tools, and cloud/edge computing platforms, also noting the level of integration with existing infrastructure and protocols (e.g., IEC 61850, Modbus).
- Performance metrics, which documents the evaluation framework used to validate the DT system. This included the type of validation (real-time simulation, hardware-in-the-loop) and potential performance metrics reported (accuracy, latency, simulation fidelity).

This layered approach enabled us to move from broad thematic insight to detailed technical synthesis. Moreover, it allowed us to identify specific gaps and inconsistencies in evaluation methodologies and highlight opportunities for cross-cluster innovation and interdisciplinary integration.

The remainder of this review presents the synthesized findings from these 32 papers, as shown in Table 2, reflecting their contributions across the core dimensions described above. Each of the table entries is also categorized (colored) as per the cluster from the co-occurrence map they belong to.

Based on this analysis, we can observe that, while research on DT technology in the power and energy sector has grown significantly in the recent years, there is a strong need for more intelligent, adaptive, and secure management of the increasingly complex grid systems. The analyzed studies demonstrate a wide variety of applications, ranging from component-level simulations to enterprise-wide planning tools, with varying levels of implementation maturity, technological integration, and performance evaluation metrics.

Abo-Khalil [3] presents a real-time hybrid simulation platform designed to analyze voltage stability and dynamics, reflecting the increasing importance of DTs in operational decision support. Similarly, Bassey [33] focuses on renewable energy systems, using DTs for component-level simulation and testing. These studies exemplify the trend of applying DTs to specific technical challenges within the power system lifecycle, particularly in generation and control. They focus on system-level modelling, reflecting the research concentrated within the blue cluster of the co-occurrence analysis and semantic mapping in the previous section. These contributions are pivotal in validating DTs as real-time, closed-loop tools rather than static digital replicas. However, while component and system-level control are well represented, the literature shows fewer examples of multiscale or federated architectures that integrate control functions across layers (component ↔ system ↔ enterprise). In contrast, Bai and Wang [19] adopt a more conceptual approach, proposing an architectural framework for intelligent power grid development using DTs. Their analysis incorporates technologies like big data, IoT, and AI, positioning DTs as foundational to broader Smart Grid initiatives. This reflects an important direction in the literature where DTs are not merely reactive monitoring tools, but strategic enablers of long-term system intelligence and interoperability. These studies are representative for the red cluster from our co-occurrence analysis, structured around the decision-making and enterprise-level

Table 2
Detailed analysis of the most relevant studies (entries are color-coded depending on which cluster they belong to, with the exception of [30], which belongs to both blue and green cluster).

Study	Study focus	Implementation type	Grid application area	Key technologies	Performance metrics
[19]	DT structure and key technologies for intelligent power grid	Hybrid	Enterprise-level intelligent operation of the physical grid	Big data, cloud computing, IoT, AI	Conceptual and structural analysis
[31]	Power consumption and productivity balance	Hybrid	Data flow between the factory and its DT	Siemens Tecnomatix plant simulation v2201, Shelly 3EM energy sensors, Mosquitto MQTT broker v2.0.15, Telegraf agent v1.24.2, InfluxDB v2.4.0, Plantsim Python	Monte Carlo cross-validation; mean, standard deviation; two-sample *t*-test, real-time data management toolchain
[32]	Microgrid management of energy demand	Hybrid	Microgrid, peak shaving	Nissan electric vehicles, bi-directional charging stations, stationary battery system	Integration of the vehicles into a car-sharing system
[3]	Power system stability	Hybrid	Voltage/dynamic stability, predictive maintenance, renewable energy integration	Real-time hybrid simulation platform	Voltage and stability analysis
[33]	Enhanced design and testing of renewable energy systems	Hybrid	Renewable energy sources – solar and hydroelectric power	MATLAB/Simulink, ANSYS, COMSOL Multiphysics, CAD software, Microsoft Azure IoT, and AWS IoT Core	Simulation-based validation of component performance
[14]	Energy management systems	Hybrid	Grid state estimation, stability analysis	SCADA, Wide Area Monitoring Systems (WAMS), Digital Dynamic Mirror	Case study
[34]	Power grid, State estimation	Data-driven	Medium and low-voltage distribution networks	Artificial neural network (ANN), harmonic spectra	Field test
[35]	Islanding control in distribution systems	Hybrid	Grid state estimation, islanding control	SCADA	Evaluation on actual energy distribution system
[36]	Voltage control in distribution networks	Data-driven	Voltage control, stability analysis	AI/ML	Validation on real low-voltage network
[37]	Distribution voltage regulation	Hybrid	Distribution grid management	ProDROMOS, Particle Swarm Optimization, OpenDSS	Real-time simulation, field demonstration
[38]	DT prototyping	Physics-based	Renewable energy integration, grid stability	PMUs, Real-Time Digital Simulator, GTNET-SKT card	Real-time simulation, hardware-in-the-loop
[39]	Hierarchical DT architecture	Hybrid	Distribution grids	Real-time interface, RT simulation environment, Opal-RT	Real-time simulation, hardware-in-the-loop
[40]	Degradation monitoring and fault detection	Physics-based	Power electronic converters	Matlab/Simulink, Simscape toolbox, Wavelet scattering, SVM	DT simulation of the power electronic converter
[15]	Cybersecurity analysis	Hybrid	Smart Grid cyber-physical system	MATLAB/Simulink, Raspberry Pi, communication protocols (Modbus, IEC61850, MQTT)	Real-time simulation, hardware-in-the-loop
[16]	Cybersecurity monitoring	Data-driven	Smart Grids	FIWARE, Security Information and Event Management (SIEM)	Real-world case study
[41]	Microgrid security	Physics-based	Microgrid security	Legacy-comm. techniques and WAMs	Simulation example
[42]	Grid anomaly detection	Data-driven	Transmission systems	WAMs, PMUs, deep learning Convolutional Neural Network (CNN)	Validation on IEEE 9- and IEEE 39-bus standard benchmarks
[43]	Cybersecurity testing and research	Hybrid	Micro-grid systems	SPEEDGOAT, MATLAB-Simulink, virtual machines, Docker containers	Real-time simulation
[44]	Energy cyber-physical systems	Hybrid	Grid state estimation, stability analysis	AWS, IoT	Real-time implementation
[45]	Replication and analysis of realistic multi-stage cyberattacks on Smart Grids	Hybrid	Cybersecurity in active distribution grids	Pandapower, Docker containers, Containernet, IEC 60870–5-104 and Modbus protocols	Real-time simulation, hardware-in-the-loop
[46]	Real-time cyber-physical analysis	Physics-based	Power distribution systems	Hardware-in-the-loop	Hardware-in-the-loop testbed
[4]	Microgrid concepts and applications	Hybrid	Microgrids	Sensor networks, IoT, high-fidelity models and simulation platforms	Comparative analysis of DT applications in microgrids
[13]	Active distribution networks	Data-driven	Distribution network management	Real-time monitoring, digital simulation frameworks	Continuous operation over a month
[47]	Networked microgrids	Data-driven	Networked microgrids	Blockchain, LSTM-based controller	Hardware-in-the-loop simulations
[48]	Radio-mesh smart meter network	Data-driven	Outage management in low voltage area	DT of radio-mesh smart meter network	Experimental data comparison
[49]	Energy hub management and grid resiliency	Data-driven	Grid stability and resilience, water-power system	Amazon Cloud Service, Bat-based optimization algorithm	Real-time simulation, hardware-in-the-loop
[50]	Dynamic thermal rating of transmission lines	Hybrid	Transmission lines of the power system	Python, scikit-learn library	Prediction accuracy, dimensionality reduction with feature selection, error correlation analysis
[51]	Promote hydrogen and accelerate the energy transition through Power-to-Gas (P2G) technologies	Hybrid	P2G tech. and regenerative hydrogen fuel cells into the electricity transmission system	PyPSA, OSeMOSYS, Pandapipes, Python-based MLOps framework with XGBoost, Random Forest, NBEATS, TCN, and LSTM. Streamlit, Apache Superset, MATRYCS Visualization Engine, Keycloak	Multi-resolution simulations and optimization
[52]	DT-enabled smart microgrids (DT-SMGs)	Hybrid	SMG system, substation and feeder automation, distributed energy management	N/A	Comparative study on situational awareness, security, and resilience

(*continued on next page*)

Table 2 (*continued*)

Study	Study focus	Implementation type	Grid application area	Key technologies	Performance metrics
[53]	Resilient power distribution systems	Hybrid	Renewable energy integration, grid stability	10 MW battery energy storage system, 2 MW photovoltaic plant, 5 MW conventional synchronous generator, NS-3 network simulator, GTNETx2 card	Electromagnetic transient simulations using real-world test case
[54]	Microgrids	Data-driven	Microgrid operations	Deep reinforcement learning	Optimization scenario
[30]	Smart Grid estimation	Physics-based	Grid state estimation, renewable energy integration	IoT sensors, computer-aided tools	Real-time simulation, hardware-in-the-loop

problems for using DT technology. However, the analysis shows limited work that integrates DTs with financial modeling, ESG metrics, and regulatory compliance in the sector. These domains are expected to grow as utilities adopt DTs for broader organizational strategy.

Several papers address the integration of DTs into distributed and decentralized grid contexts. Bazmohammadi et al. [4], for instance, explore hybrid implementations of DTs in microgrids, comparing various architectures and their operational performance. Moreover, they highlight the role of DTs in carbon accounting and demand response. Bragatto et al. [13] extend this further by exploring real-time monitoring applications, emphasizing the role of DTs in system resilience and safety assurance, as well as in environmental and economic modelling. These hybrid approaches, combining physical testbeds with digital simulations, are crucial in validating DT frameworks for environments that demand both real-time responsiveness and cyber-physical coordination. This aligns with the yellow cluster, confirming the DTs growing use for supporting sustainability metrics and demand-side flexibility. However, there remains a lack of standardization in how performance is evaluated, and very few studies explicitly incorporate environmental impact as a core metric.

Finally, a growing subset of DT research focuses on the integration of cyber-physical security measures. Several studies highlight the use of DTs for passive monitoring and active detection of system anomalies. For instance, the work by [38] explores anomaly detection frameworks within DT environments, underlining their importance in safeguarding grid assets from cyber threats such as false data injection. These contributions align with the green cluster in the co-occurrence network, emphasizing the increasing importance of cybersecurity measures. However, the literature review also reveals that, while security is recognized as a critical feature, very few studies implement real-time intrusion detection or resilience simulations as part of their DT architectures, as well as inclusion of the DT as part of the security-by-design practices. Moreover, security features are rarely integrated into enterprise-level DTs. This marks an important gap in the current body of applied research.

From a technological standpoint, most studies integrate a mix of simulation environments, communication protocols, and analytics platforms. Key technologies such as AI/ML, cloud-edge computing, and co-simulation platforms, although frequently mentioned, are unevenly adopted. Moreover, performance metrics vary widely, with some studies providing quantitative evaluation based on system stability, latency, or power flow accuracy, while others relying on conceptual validation or comparative analysis. This confirms the earlier findings about the need for standardized metrics and benchmarks to evaluate DT implementations and ensure replicability and cross-compatibility. Additionally, the literature also reveals a fragmented landscape and disparities in implementation types with many DT implementations remaining simulation-based or conceptual, and few operational deployments or validation in industrial settings.

The overall analysis of the research field is indicative of the fact that future DT research should lie in cross-domain solutions that are not only technically robust, but also secure, economically viable, and environmentally aligned. The following sections introduce such an approach.

4. A novel taxonomy of digital twins for power grids

Based on the foundational taxonomy of DTs proposed by van der Valk et al. [10], which outlines key dimensions and characteristics, and the insights obtained from the contextually relevant comprehensive analysis of the energy domain, in this section we propose an upgraded and revised taxonomy tailored specifically to DT-supported power grid systems. This new taxonomy reflects both technological advancements and evolving application domains within the power sector, and addresses several gaps and advances from the van der Valk's model: 1) It incorporates domain-specific features for energy systems, such as power electronics, grid balancing, and cybersecurity; 2) It introduces maturity, intelligence level, cyber-physical security, and data architecture as critical differentiators; and 3) It reflects real-world DT deployments in enterprises and the growing role of DTs in strategic planning and carbon reduction.

Next, we introduce the novel taxonomy of DT for power grids, outlining the revisions made to each dimension in comparison with Van der Valk's taxonomy (Fig. 1) and highlighting the addition of new dimensions that extend its scope.

4.1. [D1] data Link – extended dimension

The **Data Link** dimension is foundational to any DT system, particularly in the context of power grids, where real-time responsiveness, system-wide synchronization, and control accuracy are paramount. It characterizes the directionality and functional richness of the information exchange between the physical system and its DT. This property fundamentally shapes the DT's ability to support responsive, intelligent, and secure operation across the system lifecycle, including critical stages such as design, commissioning, and live operation.

In its simplest form, the data link can be *one-directional*, where data flows only from the physical system to the DT or, conversely, from the digital model to the physical asset. In such cases, the DT operates primarily as a monitoring or simulation tool, passively reflecting the current state of the physical environment or serving as a planning interface. Such DTs are valuable in early grid design and planning stages or when cybersecurity or regulatory constraints limit outbound control actions. For example, in commissioning scenarios involving critical infrastructure or third-party vendors, unidirectional data flow may serve as a safety mechanism during initial system evaluation [55].

In a *bidirectional* dataflow mode, the DT continuously receives sensor data from the physical grid infrastructure and, in turn, communicates back refined insights, optimization commands, or updated model parameters. This two-way exchange enables a dynamic feedback loop that supports adaptive learning, responsive control, and decision-making grounded in up-to-the-moment system conditions.. This interactive capability is essential in remote, semi-physical and virtual commissioning scenarios, where DTs interface with physical test benches or field devices, validating control logic or system behavior before full deployment [56]. In such applications, DTs can simulate fault injection, test recovery strategies, or assess compliance with performance targets, all in near-real time. These functions provide a robust digital backbone for managing complex, geographically distributed infrastructure projects.

A further evolution of this concept is the emergence of *closed-loop actuation*, where the DT does not merely inform or suggest actions, but directly controls the physical system based on real-time analytics, simulations, or AI-driven decisions [1,6]. In this configuration, the DT functions as an autonomous agent, continuously optimizing system performance by adjusting operational parameters without requiring manual intervention. This mode is especially relevant for critical grid functions like voltage regulation, frequency stabilization in low-inertia systems, or immediate cybersecurity responses to detected anomalies.

With this revision, *the Data Link dimension describes a continuum from static observation to active intervention*, reflecting the growing role of DTs not just as passive observers but as intelligent, embedded components in the operational control loop of modern power grids. Thus, the Data Link dimension becomes more than a technical descriptor – it underpins the resilience, traceability, and interoperability required in modern energy systems. These properties create an auditable and secure digital thread that spans design, testing, operation, and even decommissioning, ensuring that grid assets evolve within a continuously verifiable and context-aware digital environment. Thus, as the grid becomes more decentralized and data-rich, the ability to support bi-directional or closed-loop data links will become a defining characteristic of advanced DT architectures.

4.2. [D2] functional role − refined and extended characteristics

The **Functional Role** dimension captures the core purposes that DTs serve within power grid systems and reflects their increasing versatility across technical, operational, and strategic layers. As DT technology matures, its functional roles have expanded far beyond simple monitoring tools to encompass a broad range of applications that align with the evolving demands of modern, intelligent grid infrastructures.

At its foundational level, a DT serves a *monitoring and visualization function*, providing operators and engineers with a real-time, high-fidelity representation of the physical system. Through continuous data streams and advanced interfaces, DTs enable stakeholders to observe the status of critical assets, such as substations, transformers, or energy storage units, in both spatial and temporal dimensions. This visualization not only aids in situational awareness but also enhances transparency and system traceability. Building upon this, DTs increasingly fulfill roles in *predictive analysis and forecasting*. By leveraging historical data, physics-based simulations, and ML models, DTs can anticipate system behaviors and failures before they occur. In the context of power grids, this means predicting load profiles, identifying potential equipment degradation, and simulating grid responses to extreme weather or demand surges. This capability transforms grid management from a reactive to a proactive discipline.

Beyond prediction, DTs are now playing a proactive role in *operational control*. In real-time environments, they support the optimization of parameters such as voltage regulation, frequency stabilization, and power flow distribution [12]. This operational function is particularly critical in low-inertia systems where renewable energy sources dominate, or in decentralized grids where coordination among multiple agents is required [57]. Through integration with supervisory control and data acquisition (SCADA) systems or distributed energy resource management platforms (DERMS), DTs enable automated, real-time adjustments to ensure system reliability and performance.

Beyond operation, DTs are proving indispensable in *strategic decision support*. They serve as virtual testbeds for simulating long-term infrastructure decisions, such as transmission upgrades, energy storage integration, or market design reforms [17]. By simulating the economic and technical impacts of various strategies, DTs assist utility managers, regulators, and investors in making data-informed decisions that align with regulatory requirements and sustainability goals. Moreover, with the rise of generative and human-centric AI, the functional role of DTs is transitioning from decision support to decision co-creation. Drawing on recent advancements in diffusion models, large language models, and context-aware simulation engines [58,59], DTs can now participate in generative design tasks, offering system reconfigurations, asset layouts, or mitigation plans that were not explicitly pre-programmed. For instance, a DT embedded with generative AI can iteratively propose transformer configurations optimized for both thermal constraints and environmental exposure, or simulate the policy impact of grid tariff reform under changing usage patterns and climate scenarios.

This emergent functionality aligns not only with the Industry 5.0 concept, but also with the Society 5.0 paradigm, which emphasizes human-centric, resilient, and sustainable technological ecosystems [60]. In this context, DTs act not only as analytical engines but as co-creative collaborators, facilitating interactive planning sessions, cross-disciplinary risk assessments, and participatory decision-making. Through natural language interaction and intuitive visualization interfaces, generative DTs can communicate complex grid behavior to non-experts while still providing high-resolution simulations for engineers and analysts.

A more recent but increasingly vital function of DTs is in *cybersecurity and threat detection* [12,17]. As identified in our semantic analysis, this function is rapidly emerging as a distinct research and application area. DTs are being used to simulate cyber-physical attacks, detect anomalies in data streams, and respond to events like false data injection. They offer a platform for testing defensive strategies without risking live systems, making them central to resilience planning in critical infrastructure. As a result, *the Functional Role dimension highlights the multi-layered utility of DTs in power systems, from passive monitoring and predictive forecasting to autonomous control, strategic planning, and generative co-design; and from physical integrity to cyber resilience*. This breadth of functionality is what makes DTs not just tools, but strategic assets in the ongoing digital transformation of energy systems, especially when embedded within human–machine symbiotic workflows.

4.3. [D3] synchronization frequency − expanded beyond binary logic

The **Synchronization Frequency** dimension refers to the temporal resolution and responsiveness with which a DT maintains alignment with its physical counterpart. In the context of power grid systems, where conditions can change rapidly due to load fluctuations, renewable intermittency, or fault events, synchronization frequency is a critical determinant of the twin's utility and effectiveness [38]. Traditional approaches to synchronization have often adopted a binary logic: either the DT is real-time, or it is not. However, modern power systems demand a more nuanced taxonomy that reflects the varying degrees of temporal coupling between the virtual and physical layers. This upgraded framework introduces a gradient of synchronization modes that accommodate diverse grid applications and technological capabilities.

At the highest level of temporal precision is *real-time synchronization*, typically operating on a sub-second scale. This is essential in high-frequency control scenarios such as automatic generation control (AGC), voltage stability management, or protection relay coordination. Real-time synchronization allows the DT to serve as a live proxy for operational decisions, enabling autonomous response mechanisms, continuous model updates, and immediate actuation feedback. The deployment of PMUs and advanced IoT sensors makes this form of synchronization increasingly feasible, especially in transmission systems.

A slightly more relaxed mode is *near real-time synchronization*, where updates occur at intervals ranging from several minutes to a few hours. This mode is common in applications like dynamic network reconfiguration, predictive maintenance scheduling, and load forecasting. It provides sufficient temporal resolution for decision-making without the computational overhead of continuous streaming, making it ideal for distribution networks and enterprise asset management systems. Batch updates, on the other hand, represent a periodic synchronization mode where the DT is refreshed based on scheduled intervals, such as daily or weekly data uploads. Though limited in responsiveness, this approach remains valuable for strategic planning, long-term forecasting, or regulatory reporting – use cases where instantaneous feedback is not required but historical accuracy and model completeness are still critical.

Lastly, *asynchronous synchronization* refers to event-driven updates that are triggered by specific changes in system conditions, such as a fault detection, a topology change, or a cyber-incident. This mode allows DTs to remain dormant or lightly engaged until prompted by a relevant system event, at which point they activate to simulate, assess, or respond to the anomaly. Asynchronous DTs are particularly useful for anomaly detection systems, emergency response simulations, or non-continuous assets like backup generation units.

The Synchronization Frequency dimension captures the temporal agility of a DT and aligns it with the operational demands and computational resources of its application environment. By moving beyond a binary classification, this expanded framework offers a more flexible and realistic model for deploying DTs across diverse layers of the power grid, ranging from milliseconds-level automation to strategic-level assessment.

4.4. [D4] intelligence level – Newly defined dimension

The **Intelligence Level** is a newly introduced dimension in the DT taxonomy, designed to reflect the integration of AI and ML into the architecture and behavior of DTs, particularly within the context of complex, data-rich systems like modern power grids [61]. As DTs evolve from passive digital replicas into active, learning-based agents, their intelligence level becomes a defining characteristic of their functionality, autonomy, and strategic value [62].

At the foundational level, a DT may exist as a *static model*. This type of twin serves as a one-time or periodically updated digital representation of the physical asset or system, built using predefined rules, historical data, or physical equations. While static models can support basic visualization, planning, and simulation tasks, they lack the ability to adjust or evolve in response to changes in system behavior, external environment, or operating conditions. Their utility is therefore limited to scenarios where system dynamics are either slow-changing or non-critical.

More advanced are *data-driven adaptive models*, which incorporate real-time or historical data to update the model parameters or outputs dynamically. These DTs rely on ML algorithms to learn from incoming data streams and can adapt their behavior based on changing grid conditions. For instance, they may adjust forecast models for load prediction, refine failure probabilities for equipment, or recalibrate control strategies based on usage trends. Though not self-evolving, adaptive models demonstrate significant improvements over static twins in terms of responsiveness and relevance.

Pushing the boundaries of DT intelligence, *self-learning DTs* represent a significant leap towards autonomy and adaptability [63]. These twins employ continuous retraining and reinforcement mechanisms, enabling them to update their internal models iteratively as new data streams emerge. Such capabilities are especially valuable in non-stationary environments, such as those with high penetration of renewables, evolving load patterns, or frequent cyber-physical disturbances, where conditions cannot be fully captured by a static or periodically trained model. Self-learning DTs are able to detect emerging system behaviors, improve prediction accuracy over time, and even suggest context-dependent strategies, without the need for constant human supervision.

The most sophisticated class within this dimension is the *cognitive DT* [64], including a special subclass of generative DTs [65]. These twins go beyond learning from data and are capable of autonomous reasoning, inference, and decision-making. The inclusion of generative AI technologies, such as LLMs and diffusion models further extends their role from predictive analytics to creative co-design and context-aware interaction, allowing DTs to synthesize novel design solutions, generate simulation scenarios, and mediate natural communication between humans and machines[58]. This integration fosters human-digital symbiosis, where the DT becomes not only a mirror of system behavior, but an intelligent collaborator capable of reasoning through dialogue, generating alternative operational strategies, or even producing adaptive visualizations and engineering blueprints.

In the context of power systems, a cognitive-generative DT could autonomously propose optimal reconfigurations of the grid in response to market or stability fluctuations, simulate resilience strategies under novel cyber-attack vectors, or interact conversationally with operators to co-design contingency responses. Through such human-in-the-loop co-creation, the DT evolves into a cooperative intelligence system that augments human decision-making with generative reasoning capabilities rather than replacing it.

This Intelligence Level dimension thus provides a continuum from passive replication to full autonomy through cognitive creativity, offering a framework for evaluating DT architectures across stages of intelligence maturity in the increasingly complex and decentralized grid environments. As AI capabilities mature, the trajectory clearly points toward more intelligent, self-governing and generative DTs embody the Industry 5.0 vision – systems that are not only autonomous but human-centric, context-aware, and creatively adaptive [59].

4.5. [D5] model granularity – Revised from model accuracy

The **Model Granularity** dimension, revised from the earlier notion of model accuracy, reflects the level of abstraction at which a DT operates within the power grid domain. While accuracy remains important, this refined dimension emphasizes the scope and scale of the digital representation, ranging from highly localized asset-level models to comprehensive enterprise-wide simulations. This shift is particularly important in power systems, where DTs are applied across vastly different physical and organizational layers, each requiring tailored models to suit their functional purpose [40].

At the most detailed level, a DT may operate at the *component level*, simulating individual grid assets such as transformers, power converters, circuit breakers, or inverters. These twins often employ high-fidelity physics-based models and are essential for tasks like fault diagnosis, thermal monitoring, and lifetime prediction. Because they interact closely with sensor data and real-time control systems, component-level twins must strike a balance between computational efficiency and physical accuracy.

Stepping up in abstraction, *system-level DTs* model entire subsystems, such as distribution feeders, substations, or microgrids. These twins integrate multiple components and simulate their interactions under various operational conditions. They are instrumental in tasks such as load balancing, voltage regulation, and real-time control strategy implementation. System-level granularity allows for capturing emergent behavior that arises from the interaction of multiple components, insights that would be missed at the component level.

At the top of the organizational hierarchy are *enterprise-level DTs*, which abstract and integrate multiple systems across a utility's service territory. These models are used for long-term planning, investment analysis, risk management, and regulatory compliance. Unlike lower-level twins that focus on physical and operational parameters, enterprise-level twins incorporate economic, environmental, and organizational data, enabling strategic decision support. They are particularly important in regulatory reporting, demand forecasting, asset fleet management, and carbon accounting.

Finally, the emergence of *multi-layered DTs* signals a growing trend toward hierarchical integration, where models across different levels of granularity are interoperable and dynamically synchronized [57]. In such configurations, a fault identified in a component-level twin can trigger updates in the corresponding system- and enterprise-level models, ensuring consistent and holistic situational awareness. This approach enables scalable decision-making across technical and managerial domains, from sub-second operational control to decades-long asset investment cycles.

In essence, *the Model Granularity dimension captures the scalability and contextual relevance of a DT, aligning its structure with its intended use*. It acknowledges that no single level of abstraction suffices for the diverse challenges faced in modern power grids, and that truly effective DT ecosystems must support seamless navigation across multiple layers of complexity.

4.6. [D6] data architecture – Newly defined dimension

The **Data Architecture** dimension has become increasingly critical in the taxonomy of DT systems, especially as power grids grow more decentralized, data-intensive, and reliant on interconnected devices and services (ISO/IEC 30186, 2025). This dimension captures the infrastructure and computing paradigms that support how DTs collect, store, process, and exchange data. It plays a pivotal role in ensuring that DTs are not only operationally effective but also trusted, resilient, and adaptable across the stages of design, commissioning, operation, and retirement [2].

One foundational category within this dimension is *edge-based processing*, where data is acquired and analyzed locally, often at or near the physical asset itself, using embedded computing resources. In power grids, this enables real-time analysis and control at substations, smart meters, or renewable energy units without the delays associated with remote data transmission. Edge-based DTs are particularly useful for latency-sensitive applications such as fault detection, protection relay coordination, or adaptive inverter control, where split-second decisions are required. They also reduce bandwidth usage and mitigate data privacy concerns by minimizing cloud dependencies. During commissioning phases, edge DTs can autonomously verify physical installation parameters, monitor configuration validity, and support safe system bring-up without requiring full cloud connectivity, enhancing reliability and independence in field conditions [66].

Complementing this approach is the *cloud-integrated DT*, in which data storage, model training, and computation are offloaded to centralized or distributed cloud platforms. Cloud integration offers virtually unlimited computational resources and facilitates access to historical data lakes, AI model retraining, and long-horizon simulations. In utility-scale systems, cloud-based DTs enable enterprise-level visibility and coordination across geographic regions, supporting activities like fleet management, strategic forecasting, and regulatory reporting. This architecture is optimal for non-time-critical tasks that require complex processing and large-scale data aggregation.

An emerging and powerful paradigm is the *federated DT architectures*, which reflects the need to balance decentralization with collaborative intelligence. In a federated system, multiple DTs, each representing different components, organizations, or jurisdictions (e.g., grid operators, DER owners, OEMs), operate independently while periodically exchanging insights, parameters, or summaries. This approach preserves data sovereignty and operational independence while enabling system-wide optimization, collaborative commissioning, and coordinated control [67]. For instance, during distributed asset rollouts (e.g., battery installations across municipalities), federated DTs allow coordinated performance tuning and anomaly detection without compromising proprietary data, enhancing trust and scalability in national grid digitization efforts.

A complementary enabler of trust and governance is *blockchain-enabled data governance*. By leveraging distributed ledger technology, blockchain can ensure tamper-proof records of DT transactions, validate data provenance, and enforce access permissions through smart contracts. In the context of power systems, this supports secure peer-to-peer energy trading, transparent emissions tracking, and audit-ready compliance reporting. These features are especially valuable in semi-automated commissioning workflows involving contractors, vendors, and regulators[68]. Blockchain integration ensures that every calibration change, sensor reading, or configuration update is securely logged and verifiable, forming a transparent, auditable digital thread from installation to retirement.

Together, these architectural modes form a continuum of scalability, autonomy, and trust. *The Data Architecture dimension*, therefore, is not merely a technical consideration; it *is a strategic enabler of secure system interoperability, regulatory alignment, and human–machine collaboration*. As power systems advance toward Industry 5.0, the integration of edge, cloud, federated, and blockchain layers will be key to enabling resilient and trusted DT ecosystems that operate seamlessly across physical, organizational, and lifecycle boundaries.

4.7. [D7] interface types – Expanded with AI/Multi-agent type

The **Interface Types** dimension defines how a DT communicates and interacts with both human actors and technical systems, determining its usability, as well as its potential to become integrated, interactive agent within the broader grid ecosystem. As DTs become more embedded in complex and distributed grid infrastructures, the range and sophistication of their interfaces must evolve to accommodate increasingly diverse, decentralized, and collaborative interaction scenarios across technical and organizational boundaries [20].

The most established and widely used modality is the *human–machine interface (HMI)*, which allows operators, engineers, and decision-makers to visualize and interact with the DT via graphical dashboards, control panels, and visual analytics. These interfaces often provide real-time insights, key performance indicators (KPIs), alarm systems, and control commands. More recently, immersive technologies such as Augmented Reality (AR), Virtual Reality (VR), and digital avatars are being incorporated into DT environments, supporting enhanced situational awareness and operator training. These developments mark the convergence of DTs with the Industrial Metaverse, a virtual space where physical infrastructure, data, and human agents interact in real-time [69]. Such metaverse environments are core enablers of Industry 5.0, prioritizing human-centric, resilient, and sustainable systems. Through immersive HMI, DTs can now enable spatially contextualized simulations, like virtual walkthroughs of substations or live debugging of control room operations, thereby augmenting decision-making and maintenance precision [70].

Beyond human interaction, *machine–machine interfaces* enable DTs to exchange data and commands autonomously with SCADA systems, Energy Management Systems (EMS), or DERMS. In these contexts, DTs become active nodes within automated control loops, supporting functions such as real-time dispatch optimization, grid balancing, and fault recovery. Such seamless machine-to-machine integration is vital for ensuring speed, reliability, and scalability in dynamic grid environments.

A third and increasingly important mode of interaction, especially in decentralized or transactive energy systems, is *multi-agent interaction* [71]. In this configuration, DTs operate as not just individual assets, but semi-autonomous or agents capable of negotiating, cooperating, or competing with other DTs and systems. For example, DTs of DERs may interact in real time to optimize local energy exchange, perform peer-to-peer trading, or jointly stabilize voltage in a microgrid. These multi-agent interactions rely on decentralized communication protocols, semantic interoperability, and increasingly generative AI-based logic. As part of the Industrial Metaverse vision, these multi-agent interactions may be embedded within shared virtual environments, where stakeholder teams, comprising technical experts, business strategists, and regulatory bodies, can collaboratively explore and simulate strategic or operational decisions [72].

These interface types highlight the evolving role of DTs from isolated modeling tools to interactive, multi-modal platforms embedded in both human workflows and automated control ecosystems. *The Interface Types dimension thus encapsulates the DT's capacity not only to inform but also to engage, coordinate, and act,* enabling smarter, more agile, and more human-centered energy systems.

4.8. [D8] lifecycle Positioning – Revised from time of creation

The **Lifecycle Positioning** dimension defines the temporal relationship between a DT and its corresponding physical system across the asset's life cycle. This dimension captures when the DT is developed and how it evolves in relation to the physical grid component or system it mirrors [18]. It reflects the expanding role of DTs not only as operational tools but as integrated assets that support engineering, deployment, monitoring, and retirement across the entire life span of power infrastructure [73].

One of the most strategic uses of DTs is in the pre-physical phase, often referred to as *DT-before physical*. In this configuration, the DT is developed during the design or prototyping stage, long before the physical component or system is built. This allows engineers and planners to simulate grid behavior under varying scenarios, evaluate component compatibility, and validate safety or compliance requirements, all without the cost or risk of physical deployment. In power grid planning, such digital pre-representations are used to model substation layouts, test protection schemes, or assess renewable integration feasibility before committing to capital investment. Recent advancements also demonstrate how DTs can enable remote, semi-physical commissioning, as explored by Leng et al. [55], through integration with sensor streams and hardware-in-the-loop simulation, allowing virtual testing of control strategies under near-operational conditions.

A growing trend in smart grid infrastructures is the *simultaneous development* of the DTs and its physical counterpart. In this mode, the DT evolves in parallel with its physical twin, with each informing the other's progress. For instance, during the construction of a power plant or large-scale microgrid, the DT can be updated with real-time construction progress and commissioning data, while feeding back optimization suggestions and error detections. The ManuChain II project exemplifies how this paradigm promotes digital trust and coordination across multiple actors and locations [68,74], which is an essential capability for grid modernization initiatives involving multi-vendor and transboundary infrastructure.

In many existing grid environments, however, physical assets are already in operation. In such cases, a *DT-after physical* approach is applied, whereby the DT is created retrospectively. These retrofitted DTs often rely on historical data, SCADA logs, or sensor retrofits to reconstruct operational behavior and asset condition. This is especially common in legacy infrastructure or brownfield projects,[2] where the goal is to extend asset life, improve operational efficiency, or introduce predictive maintenance without replacing the physical equipment. Although limited in temporal continuity, this approach still benefits from digital enhancements like AI-assisted anomaly detection or retrospective cybersecurity assessments [75].

The most advanced and holistic approach is the *lifecycle-integrated DT*, which is designed to accompany the physical system from its conceptualization through to its decommissioning. Such twins evolve alongside the asset, continuously ingesting data, updating models, and supporting various stakeholders, engineers during design, operators during use, and analysts during retirement planning or asset replacement. In power grids, lifecycle-integrated DTs are foundational for implementing full asset performance management (APM) systems, supporting regulatory compliance, and enabling end-to-end traceability for carbon and cost accounting. When enhanced with features like blockchain-secured records and contextual human-AI collaboration, such DTs directly support the resilience, transparency, and human-centricity goals of Industry 5.0 [74]. Their importance is increasingly recognized in regulatory compliance workflows, carbon tracking, and cross-sector planning initiatives.

[2] Brownfield projects are projects where some work has already been made. The site is already partly developed with the required infrastructure. In contrast, a greenfield project starts from scratch.

Ultimately, *the Lifecycle Positioning dimension encapsulates how embedded and sustained a DT is within the engineering and operational history of a system.* It reflects the evolution from static digital models to resilient, co-evolving systems that support complex commissioning workflows, operational optimization, and responsible decommissioning, all of which are cornerstones of the next generation of grid innovation.

4.9. [D9] application domain – Newly defined dimension

The **Application Domain** dimension, newly introduced in the expanded taxonomy, categorizes DT implementations based on their functional focus within the broader electricity system. This domain-specific classification is essential to understanding how DT technologies are being tailored to address the unique challenges, objectives, and operational characteristics of different segments of the power sector. As energy systems undergo transformations, driven by decentralization, decarbonization, and digitalization, DTs are increasingly applied across the full electricity value chain, each with distinct use cases and performance requirements [4,13].

In the *generation* domain, DTs are used to model and optimize the operation of power plants, whether fossil-based, nuclear, or renewable. For conventional plants, DTs help monitor turbine performance, manage heat rates, and predict equipment failures. In renewable generation, they are critical for wind and solar forecasting, inverter diagnostics, and hybrid system management. DTs in this domain often rely on high-resolution physics-based models and are instrumental in achieving higher plant availability and efficiency.

Within *transmission* systems, DTs play a strategic role in maintaining grid stability, managing congestion, and supporting wide-area situational awareness. These twins replicate transmission lines, substations, and control schemes to assess real-time system dynamics, validate protection settings, and simulate contingency events. Their integration with PMUs and synchrophasor data enables rapid response to disturbances and supports real-time state estimation, making them a key component in transmission system reliability and security.

In the *distribution* domain, where variability and customer interactivity are high, DTs are used to manage grid reconfiguration, fault detection, and load balancing. DMS and DERMS, providing operators with granular insights into feeder-level dynamics, voltage control, and power quality. As more behind-the-meter resources come online, distribution-level DTs are essential for enabling visibility and control in increasingly complex, multi-directional flow networks.

A particularly fast-growing area is *microgrid and DER integration*, where DTs are applied to coordinate localized energy generation, storage, and consumption. These systems require highly adaptive DTs capable of managing intermittent resources, islanding transitions, and real-time optimization. Whether for campuses, industrial facilities, or rural electrification, DTs in microgrids facilitate seamless coordination of decentralized assets, enhance energy autonomy, and improve resilience against grid disruptions.

In the emerging field of grid-to-vehicle interaction and *demand response*, DTs are used to model user behavior, forecast flexible demand, and optimize the scheduling of electric vehicle (EV) charging. These applications require integration of behavioral analytics, tariff signals, and load aggregation strategies. DTs enable dynamic demand-side participation in grid operations, supporting decarbonization and grid flexibility goals.

Finally, in *energy market modeling* and emissions management, DTs extend beyond physical system replication to include economic and environmental layers. Here, DTs simulate market behavior, pricing dynamics, carbon emissions, and policy impacts. They assist utilities and regulators in forecasting market risks, evaluating investment strategies, and supporting compliance with environmental targets, such as those related to carbon trading or ESG reporting.

The Application Domain dimension represents the versatility and scalability of DT technology across the electricity ecosystem. By aligning DT design and deployment with specific domain needs, from plant-level diagnostics to enterprise-wide market forecasting, it ensures that DTs deliver targeted, high-value outcomes tailored to the operational context in which they are embedded.

4.10. [D10] Cyber-Physical security integration – Newly defined dimension

The **Cyber-Physical Security Integration** dimension, newly introduced in response to the growing risks identified in the green cluster of our semantic co-occurrence analysis, reflects the increasingly essential role DTs play in safeguarding power systems against both cyber and physical threats. As power grids become more interconnected and reliant on digital infrastructure, they are increasingly vulnerable to a wide range of attacks, from data breaches and false data injection to coordinated intrusions targeting critical control systems [76]. DTs are now being recognized not only as operational tools but also as active security enablers within cyber-physical systems [43].

At the foundational level, DTs contribute to *passive monitoring* by continuously collecting and analyzing real-time data from the physical grid. This allows for anomaly detection techniques, often powered by ML algorithms, that can identify deviations from expected behavior, such as unusual voltage patterns, unauthorized access attempts, or inconsistencies in sensor data. Through this continuous surveillance, DTs enhance situational awareness and provide early warning capabilities, helping operators respond quickly to emerging threats or system failures.

Moving beyond detection, DTs also support *active defense* strategies, wherein they simulate specific attack scenarios, such as false data injection attacks, denial-of-service (DoS) events, or control system manipulation, to evaluate the grid's response and resilience. These simulated environments enable utilities to test the effectiveness of cybersecurity protocols, develop countermeasures, and train staff without exposing the live system to risk. Active defense DTs also contribute to the refinement of intrusion detection systems (IDS) and security policies, ensuring that protection mechanisms are tested under realistic and evolving threat conditions.

A further extension of this role lies in *resilience testing and recovery planning*. Here, DTs are employed to model cascading failures, interdependencies across infrastructure layers, and recovery timelines. These simulations allow grid operators to assess the robustness of contingency plans, identify system vulnerabilities, and optimize restoration strategies following an attack or natural disaster. The ability to conduct comprehensive "what-if" analyses within a digital environment offers a critical advantage in preparing for high-impact, low-probability events that could compromise grid integrity and public safety.

By integrating security functions into the very fabric of operational modeling, the Cyber-Physical Security Integration dimension positions DTs as proactive, multi-layered security agents. Rather than being siloed tools for engineering or planning, DTs in this capacity serve as a bridge between operational technology (OT) and information technology (IT), combining physical grid dynamics with cyber-defense mechanisms in a unified, intelligent platform. Thus, this dimension expands the strategic importance of DTs in modern energy systems, *demonstrating that their value extends beyond efficiency and reliability to encompass resilience, trust, and system integrity in an era of increasingly sophisticated cyber-physical threats.*

This upgraded taxonomy is systematized in Table 3. It provides guidance not only for academic inquiry but also for practical implementation by utilities and technology providers. It offers a systemic basis for benchmarking DT maturity, supporting the design of architectures, and identifying research and development priorities in the evolving digital power grid landscape.

To facilitate reuse and ensure practical applicability, we developed an interactive web tool in a React-based environment, which is openly available on GitHub.[3] The tool generates both an overall maturity score based on [11] and detailed maturity assessments for each taxonomy dimension. In addition to system-specific recommendations, it provides real-time feedback through visual analytics such as radar plots and heat maps, and it supports comparative benchmarking across multiple DTs. In this way, the tool serves as a decision-support instrument for both functional and operational choices. This allows us to demonstrate that the taxonomy is more than a conceptual framework: it constitutes a replicable and usable model for evaluating DT maturity and stakeholder needs in real-world contexts. The following section illustrates this through concrete use cases, which are mapped and analyzed using the taxonomy, accompanied by comparative insights and benchmarks generated by the tool.

5. Taxonomy-based use case mapping: DT maturity evaluation

To demonstrate the practical applicability of the taxonomy, this section first validates its use as a tool for systematic mapping and maturity evaluation. This validation makes it possible to identify existing gaps and to reason systematically across each dimension, resulting in targeted recommendations for design improvements. Building on this, we then perform comparative benchmarking of three real-world use cases, which illustrates the taxonomy's added value as both an analytical framework and a decision-support instrument.[11].

The selection of the maturity evaluation framework was guided by a critical review of existing models. To preserve the logical flow of the paper, the full justification for this choice is provided in Appendix A. In this section, we summarize the key properties and background of the chosen ISO standard and establish a clear correspondence between the proposed taxonomy dimensions and the maturity aspects defined in [11]. This not only positions the taxonomy within a recognized international framework, but also demonstrates how sector-specific refinements extend and complement the generic maturity model.

The [11] standard offers a generic maturity model for DTs, defining maturity levels, assessment indicators, and methodological guidance for conducting evaluations (ISO/IEC 30,186 2025). It structures maturity around five aspects: **Convergence, Capability, Integrated View, Time,** and **Trustworthiness**. Convergence reflects the degree of alignment between the physical entity and its digital representation. Capability describes how effectively the twin can mirror, simulate, predict, or infer the behavior of its physical counterpart. Integrated View measures the extent to which the twin consolidates multiple domains, subsystems, or data sources into a coherent whole. Time captures how the twin manages temporal aspects such as latency, update frequency, historical data, and future projections. Finally, Trustworthiness assesses reliability, security, data quality, robustness, and integrity of the DT. In addition to these definitions, the standard specifies assessment indicators for each aspect and outlines the practical steps required to map a given system onto the maturity model. Annex A of ISO/IEC 30,186 (2025) provides an illustrative example of this process, applying the framework to the KOEN power plant DT.[4] This example demonstrates how the indicators can be operationalized in real-world settings and thus proves the applicability of [11] as a foundation for evaluating DT maturity.

While the ISO model is deliberately generic to ensure applicability across diverse domains, this breadth comes at the cost of granularity.

[3] The open source code of the tool: https://github.com/TanjaPavleska/dt-taxonomy/tree/masterThe interactive web-hosted tool: https://anonresearcher107.github.io/digital-twin-taxonomy/.

[4] https://www.mk.co.kr/en/it/11127734.

Table 3
The new taxonomy of Digital Twins for power grid systems (green color represents the fields encoded as multiple choices in the interactive tool. This is similar to the exclusivity dimension in Van der Valk's taxonomy, only there the green denotes mutual exclusiveness; *denotes newly added dimension).

Dimension	Characteristics					
Data Link	One-directional	Bi-directional	Closed-loop actuation			
Functional Role	Monitoring and visualization	Predictive analysis and forecasting	Operational control	Strategic decision support	Cybersecurity and threat detection	
Synchronization Frequency	Real-time	Near real-time	Batch updates	Asynchronous		
Intelligence Level*	Static model					
	Data-driven adaptive model	Self-learning DT	Cognitive DT			
Model Granularity	Component-level	System-level	Enterprise-level	Multi-layered		
Data Architecture*	Edge-based processing	Cloud-integrated DT	Federated DT architecture	Blockchain-enabled data governance		
Interface Types	Human-machine	Machine-machine	Multi-agent interaction			
Lifecycle Positioning	DT-before physical	Simultaneous development	DT-after physical	Lifecycle-integrated DT		
Application Domain*	Generation	Transmission	Distribution	Microgrid/DER integration	Demand response	Energy market modeling
Cyber-Physical Security Integration*	Passive monitoring	Active defense	Resilience testing & recovery planning			

Domain-specific challenges, such as safety requirements in critical infrastructure DTs or strict real-time constraints in industrial systems, are not fully captured in the standard's assessment indicators. Moreover, although the standard provides "assessment indicators," many remain qualitative or semi-quantitative, which leaves room for subjectivity and inconsistency between assessors. The inclusion of Trustworthiness is both necessary and forward-looking, yet its operationalization in practice remains difficult: balancing security, data integrity, resilience, and robustness against functional performance is not a trivial task. In addition, real-world DTs rarely evolve along all dimensions in a linear fashion, and the ISO framework may oversimplify the complex trade-offs and interdependencies between aspects. Because improvement in one area often has cascading effects on others, drawing clear recommendations from the generic ISO model can be challenging. Our taxonomy addresses these limitations by adding specificity and translating the ISO aspects into the realities of the energy sector. For example, cyber-physical security is treated not merely as a generic trust-related concern but as a direct operational dimension of DTs in the grid context. At the same time, the taxonomy preserves compatibility with [11], ensuring that every dimension maps to one of the ISO maturity aspects. This correspondence is presented in Table 4, while Appendix B provides detailed explanations and the rationale for each mapping.

As the table illustrates, certain dimensions align more directly with specific ISO aspects; for example, synchronization frequency maps neatly to the Time aspect, and functional role corresponds clearly to Capability. Others, however, cut across multiple maturity aspects, such as intelligence level, which influences both Convergence (through adaptive alignment with the physical system) and Capability (through enhanced functional scope). Importantly, these mappings should not be read as one-to-one equivalences, but rather as indicating relationships in scope and focus between the taxonomy and ISO 30186. In some cases, the taxonomy provides a more detailed or domain-specific view: for instance, the ISO aspect of Trustworthiness is narrower than the taxonomy's Cyber-Physical Security dimension, while synchronization frequency can be considered a specific operational subset of ISO's broader Time aspect. This relational interpretation shows the complementarity between the ISO maturity model and the proposed taxonomy, while also highlighting the added granularity and sector-specific relevance that the taxonomy brings.

5.1. KOEN digital twin in view of the taxonomy

Korea South-East Power Co. (KOEN) has developed a DT for its power generation facilities, being the first such operational plant DT in Korea. KOEN DT creates a virtual 3D model of the power plant linked with various real-world data streams. Initially deployed in 2022 for an operating thermal plant, the technology was extended to new and renewable power plants by 2023. Since 2024, the DT has been applied from the construction phase of a new Goseong natural gas power plant, integrating asset data, safety parameters, and operational considerations throughout the plant's lifecycle (design, construction, and operation). This lifecycle integration aims to improve safety and efficiency by simulating and analyzing the plant in virtual space before issues arise in reality. KOEN is also standardizing its approach through DT maturity indicators, indicating a focus on data integration (linking design models with real-time operational data), functional breadth (covering multiple use cases like construction management, asset monitoring, and safety), and consistency in modeling granularity and practices. Its primary functions include real-time monitoring of plant operations, predictive simulation of performance and failures, fault diagnosis, and decision support for operators and managers. By synchronizing physical and digital domains nearly in real time, it enables both operational oversight and strategic planning.

The KOEN DT was formally assessed using [11], and is presented by the standard as a benchmarking example of DT maturity. According to the assessment, KOEN demonstrated advanced maturity (Level 4) in *Convergence, Capability, and Integrated View*, while *Time and Trustworthiness* remained at Level 3, indicating areas for improvement. By applying the mapping shown in Table 4, we can now re-analyze KOEN through the lens of the proposed taxonomy. This serves two purposes: first, it validates the taxonomy as a practical tool for structured maturity assessment; and second, it enables the comparative benchmarking of other power grid DTs against a reference case.

Building on the description of KOEN and the available documentation, its mapping across the taxonomy dimensions is presented in column 1 of Table 5. The maturity profile of the KOEN DT, shown in Fig. 4, provides a concrete validation of the taxonomy as a tool aligned with [11] while adding the sector-specific granularity previously discussed. The assessment confirms an overall maturity score of 66.8/100, consistent with the ISO evaluation. Strong performance is visible in dimensions like Data Link, Synchronization Frequency, and Functional Role (all 80), which aligns with KOEN's demonstrated ability to integrate real-time data flows and support predictive and operational functions. By contrast, dimensions like Application Domain (33) and Cyber-Physical Security Integration (33) expose notable weaknesses, emphasizing the need for enhanced cross-domain applicability and embedded resilience mechanisms – areas that ISO groups under broader aspects like Trustworthiness. The profile also reveals intermediate scores in Intelligence Level (65), Model Granularity (60), and Data Architecture (70), indicating that while KOEN is advancing in adaptive analytics

Table 4
Mapping of Taxonomy Dimensions to ISO maturity aspects.

Maturity Aspect Dimension	Convergence	Capability	Integrated View	Time	Trustworthiness
Data Link	✓				
Functional Role		✓			
Sync. Frequency				✓	
Model Granularity			✓		
Intelligence Level	✓	✓			
Data Architecture			✓		
Interface Types		✓			
Lifecycle Positioning	✓		✓		
Application Domain			✓		
Cyber-Physical Security					✓

Table 5
Mapping the use case-DTs to the taxonomy dimensions.

Dimension	KOEN DT	Elvia DT	Bentley OU DT
Data Link	Bi-directional links between plant assets and virtual models; lifecycle integration from design to ops	Strong bi-directional data integration: smart meters, GIS, SCADA, ADMS, sensors	Multi-source ET/IT/OT integration (engineering, asset, IoT, GIS, SCADA) into unified cloud twin
Functional Role	Monitoring, predictive simulation, construction/ operation management, safety optimization	Real-time monitoring, outage management, capacity optimization, planning and flexibility operations	Monitoring, planning, design optioneering, predictive maintenance, asset/network performance analysis
Synchronization	Near real-time updates; integrated into SCADA and operational platforms	Near real-time synchronization with grid data (smart meters, AMI, SCADA); predictive 48 h simulation (FlexOps)	Continuous synchronization (4D "live" twin with time dimension) but less real-time than Elvia
Intelligence Level	Predictive analytics, simulations, but limited adaptive or autonomous learning	Advanced predictive and what-if analysis; near-term forecasting and flexibility simulations	Embedded dashboards, ML-assisted data quality and analytics; emphasis on decision support
Model Granularity	High subsystem detail (plant equipment, thermal/renewables, lifecycle models)	GIS-based, phase-level distribution network models; high-fidelity for LV systems	2D/3D asset and network models, reality models (LiDAR, photogrammetry), multi-level system integration
Data Architecture	Enterprise integration with focus on lifecycle digital threads (construction–operation)	SaaS/cloud-based ADMS integration; GIS Utility Network foundation for detailed modeling and connectivity	Cloud-based (iTwin platform), connected data environment spanning ET/IT/OT
Interface Types	Human–machine (dashboards), machine–machine via SCADA integration	Human–machine dashboards, planning/ops interfaces; machine–machine integration with ADMS and Kognitwin simulators	Multi-user visualization (immersive 4D models, dashboards); enterprise system interoperability
Lifecycle Positioning	Expanding from DT after physical to lifecycle DT (applied from construction phase in new plants)	DT after physical – covers planning, operations, and maintenance stages; extending towards lifecycle asset management	DT after physical – explicit lifecycle integration: design, construction, operation, maintenance
Application Domain	Power generation (thermal, gas, renewables); safety and efficiency focus	Distribution grid (low-voltage focus, flexibility management, outage reduction, capacity optimization)	Multi-domain: generation, transmission, distribution, and gas/water/other utilities
Cyber-Physical Security	Limited detail in public sources; expected as a maturity dimension under development	Not explicitly documented; presumed through vendor SaaS/utility-grade security practices	Enterprise-grade cloud security (Azure-based); interoperability without compromising security

and structural integration, there remains room for improvement before reaching full maturity.

The scoring mechanism draws directly on the principles from the [11] standard for DT maturity modeling. However, as discussed in the previous section, the standard's criteria are broad and non-prescriptive, which makes direct operationalization difficult in practice – particularly in complex domains like power grids. Therefore, we semantically enriched and adapted the ISO logic to fit the more concrete and systematic taxonomy dimensions developed in this work. Specifically, the scoring algorithm evaluates each selected option based on (i) its individual contribution to functional completeness, (ii) the interdependencies between selected dimensions, and (iii) embedded logical rules (e.g., if "Closed-loop" is selected for Data Link, higher maturity scores are awarded only if control and synchronization options are also present). The full logic for computing maturity levels across each dimension of the taxonomy is encoded in the file `taxonomy_rules.ts`, which is available in the public GitHub repository accompanying this research.

This multidimensional view not only confirms the validity and compliance of the taxonomy with the ISO standard, but also demonstrates its added value. In the ISO document, the KOEN use case is evaluated in a more implicit and narrative manner, without explicit scoring guidance or generalizable assessment logic. In contrast, our framework provides a systematic, rule-based, and transparent means to replicate the assessment with fidelity and extend it to other use cases across the power grid domain. In that sense, our work does not merely implement ISO logic, but it also contributes to its operationalization and advancement by concretizing the ISO principles into machine-readable and explainable logic. Thus, the taxonomy provides actionable insights by pinpointing concrete strengths and weaknesses across operationally relevant categories. This enables benchmarking across different DTs, while providing practical recommendations for targeted design improvements, as shown in Fig. 5.

5.2. Taxonomy-guided comparative benchmarking

In addition to the KOEN DT, this section examines two further implementations as use cases that are mapped to the taxonomy in order to strengthen the argument for its practical applicability: Elvia's operational DT [77] and Bentley's OpenUtilities (OU) DT [78]. The three cases are analyzed together, allowing for comparative benchmarking and simultaneous assessment of their maturity across all taxonomy dimensions. This comparative approach demonstrates how the taxonomy can reveal distinctive strengths and weaknesses, while also highlighting

Fig. 4. Maturity profile of the KOEN DT: Radar chart with a heat-map of maturity scores across dimensions.

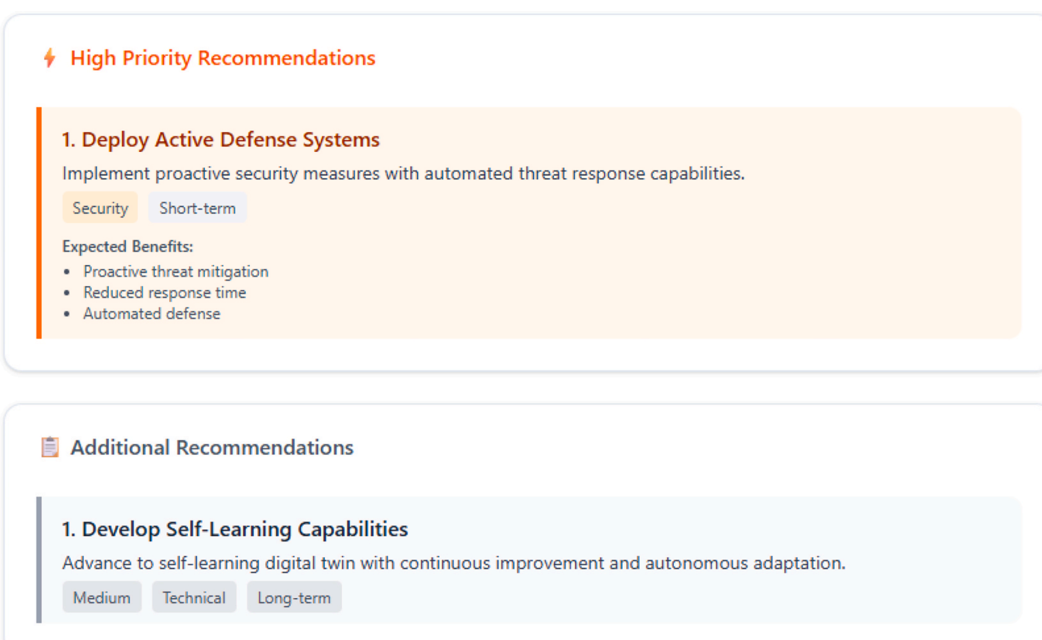


Fig. 5. Taxonomy-based recommendations for KOEN DT, as provided by the tool.

common challenges across different contexts.

The selection of use cases was made deliberately to capture a diversity of DT approaches. Elvia represents an operationally focused system, oriented towards real-time monitoring, outage management, and flexibility services at the distribution level. Bentley's OpenUtilities, by contrast, exemplifies a lifecycle-integrated platform, designed to support design, planning, and asset management alongside operational functions. KOEN provides a balanced, generation-focused solution, embedding DT practices across construction, operation, and safety optimization of power plants.

Elvia Digital Twin: Elvia,[5] Norway's largest distribution system operator, has developed a DT of its low-voltage network that integrates data from smart meters, sensors, and geospatial models into a continuously updated representation of the grid [77]. This twin is used to monitor grid conditions in real time and optimize outage management, helping operators detect faults and respond faster. The data link between live operational systems and the DT enables synchronization of the twin with the physical grid, while built-in analytics provide intelligent insights (like identifying critical network segments at risk) to fulfill the DT's functional role in outage reduction and grid reliability. Importantly, this implementation is not limited to operations; the system allows to manage the grid "from planning to operations and maintenance," indicating full lifecycle integration from network planning and design through daily operation and asset maintenance. This means that the DT supports long-term capacity planning and grid development (e.g. integrating more renewables or EV chargers) as well as immediate operational decisions, all within one platform.

This reflects the model granularity dimension; Elvia's DT is not just an abstract simulation; it's built on a detailed GIS-based network model that mirrors the real grid's topology and equipment, enabling precise analyses (for example, phase balancing issues or voltage drops can be understood and addressed in the twin). This detailed modeling, combined with live data feeds, underscores the twin's strength in data linking and synchronization (bringing together static design data with dynamic sensor/AMI data). Although cybersecurity is not explicitly detailed in these sources, it can be assumed that, as a critical infrastructure project deployed on Siemens' cloud platform and integrated with utility operational systems, robust security and access controls are in place to protect both the data link and the control interfaces (a standard requirement for modern utility SaaS solutions).

Beyond monitoring current state, Elvia's DT incorporates predictive and what-if analytical capabilities, illustrating the "intelligence" dimension of the taxonomy. It essentially serves as a decision-support tool, guiding grid operators on where and when to act (or invest in reinforcements) to maintain stability. This enhances the functional role of the twin from passive monitoring to active planning and operational optimization.

Bentley OpenUtilities Digital Twin: is a cloud-based DT tailored for electric, gas, and other utility networks [78]. It provides an architectural framework and toolset to create a digital replica of utility infrastructure, integrating data from many sources (engineering models, GIS, IoT, etc.) and enabling enterprise-level analytics. In Bentley's definition, the DT is an "immersive 4D digital representation" of physical assets and their environment, incorporating geometry and engineering data with the time dimension (continuous updates) to keep the model synchronized with reality.[6] It serves to "consolidate, validate, and align" engineering technology (ET), IT, and operational technology (OT) data into a unified, connected data environment. This means data from diverse systems (network GIS maps, substation and plant equipment models, real-time SCADA measurements, IoT sensor feeds, etc.) are brought together and contextually linked within the DT. This rich data linking breaks down traditional silos (between planning models, maintenance records, and live operations data) and provides a "single integrated network" view of the grid for all stakeholders. The model granularity can range from high-level network connectivity down to detailed assets: it supports both 2D and 3D representations, meaning a utility can see schematic diagrams as well as spatially accurate models of assets or even a reality-captured 3D context of a site. This forms the basis for analysis and decision-making.

Furthermore, the DT embeds analytics and intelligence capabilities to derive value from the aggregated data. Notably, Bentley provides predefined and extensible dashboards and analytic tools on top of the DT, allowing utilities to monitor performance metrics, run simulations, and gain insights into network behavior. These analytics can include load flow simulations, predictive maintenance algorithms, or asset health indices, all accessible in the DT's unified interface. For example, the platform provides a continuously updated simulation to assess integration of DERs and grid reconfigurations, signifying that the DT's functional role spans from real-time operations (monitoring and control support) to strategic planning and engineering analysis. It provides decision support for both asset performance and network performance across the operations and maintenance lifecycle of infrastructure. The lifecycle integration is inherent: by converging BIM/engineering models with asset management systems and live operational data, the DT creates a thread of information continuity from initial design to daily operation to eventual maintenance and upgrades. Finally, enterprise-grade cybersecurity and scalability are delivered via cloud services and are intended for mission-critical infrastructure, adhering to industry security standards (authentication, encryption, access control) to protect the sensitive grid data.

Based on these insights, the Elvia and Bentley OU DTs were mapped onto the taxonomy dimensions, as summarized in the second and third column in Table 5.

This yields the recommendations shown on Fig. 6. In the current implementation of the tool, the recommendation engine has no context-aware reasoning capabilities and contains generic recommendations, as visible from the same recommendations on deployment of active defence systems resulting from the same dimension choices for Elvia's and Beltley's DTs. This is because the scope of this study is the definition of the taxonomy and its contextualization to power grids rather than automating operational decision-making. Future iterations of the tool, however, will focus on designing adaptive and context-aware recommendation algorithms that will be able to provide more in-depth recommendations with reasoning tailored to the specific solution / DT and its operational characteristics and requirements, acting as decision-making assistants to operators and experts.

Comparative benchmarking: The mappings of each of the DTs along the taxonomy dimensions are shown on Fig. 7 and Fig. 8, representing the visualizations of the comparative benchmarking through radar chart and heat-maps, respectively, for all three use cases: KOEN, Elvia, and Bentley. As the figures demonstrate, there are different priorities and maturity profiles of these systems, which do not necessarily show immature systems, but mostly reflect the organizational and technical contexts in which they were developed.

KOEN's DT provides a balanced approach to power generation. It exhibits strong model granularity and functional roles, with detailed subsystem representation and capabilities for monitoring, simulation, and fault diagnosis. It also performs well in data linkage and synchronization, but unlike Elvia, it is less developed in cyber-physical security and lifecycle integration, reflecting its post-hoc orientation as a twin built after physical assets were already in place.

The heat-map provides a more detailed maturity assessment of the three DTs across the ten taxonomy dimensions, expressed as numerical scores and categorized into performance bands (excellent, good, fair, and needs improvement). The numbers offer a sharper perspective on where each DT excels and where it lags, complementing the radar chart view.

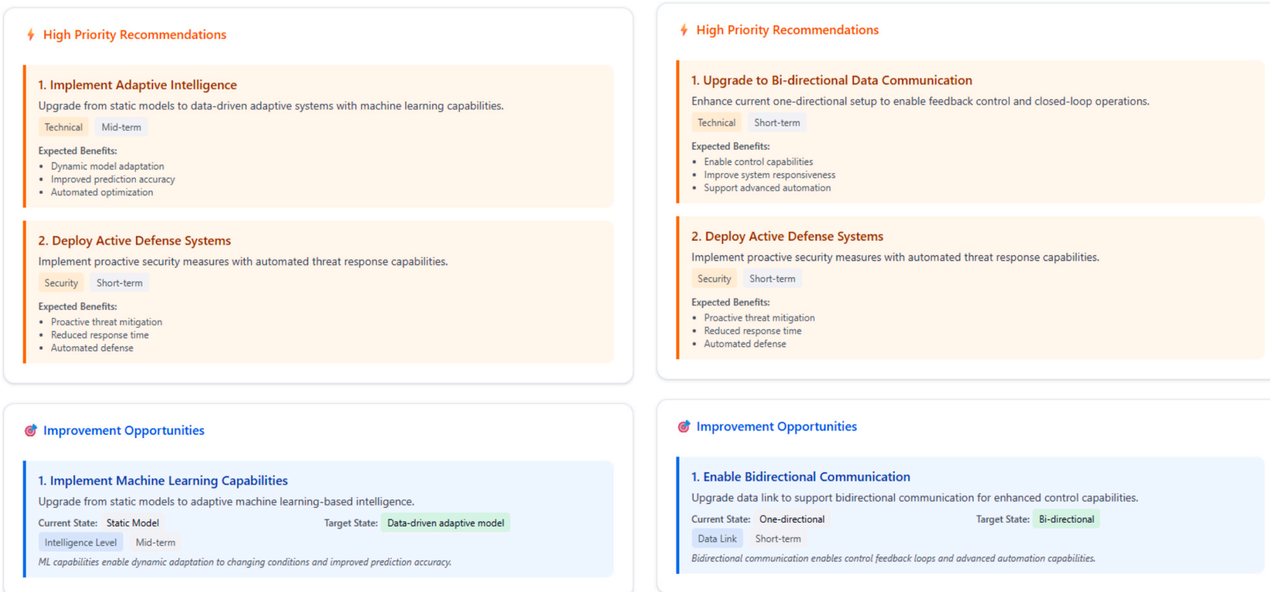
6. Discussion

6.1. Overview of contributions

The upgraded taxonomy presented in this paper provides a systematic and domain-specific lens through which DTs for power grid systems can be analyzed, benchmarked, and improved. By extending earlier generic frameworks [6,10], it addresses the gaps identified in our co-

[5] https://www.elvia.no/english?ad=forside.

[6] https://connectedtechnologysolutions.co.uk/bentley-systems-introduces-new-digital-twin-services-2/.



a) b)

Fig. 6. Taxonomy-based recommendations for a) Elvia's DT, b) Bentley's OpenUtilities DT.

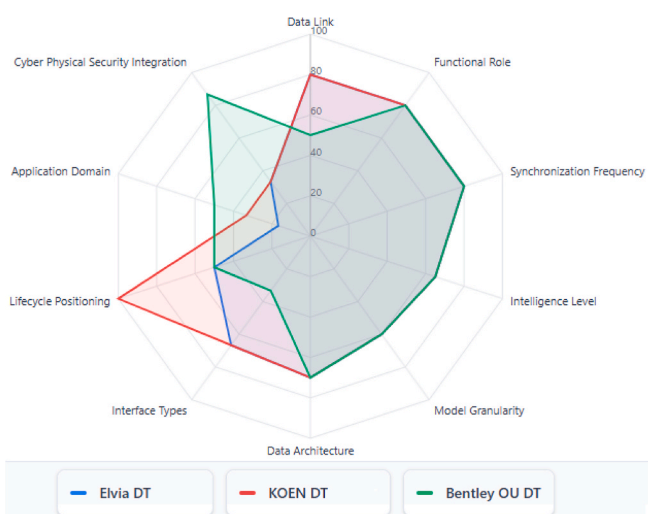


Fig. 7. Radar chart of the comparative benchmarking across DT dimensions for the three use cases(Note: All taxonomies are stored locally on a machine. Therefore, the visualization of the use cases will be shown upon adequately entering the mapping for each use case DT, as provided in Table 5, and saving them locally.).

occurrence analysis: insufficient attention to lifecycle positioning [2], limited integration of cybersecurity and resilience in critical infrastructures [79], and underdeveloped treatments of multi-layered data architectures and interface types [1]. By explicitly embedding dimensions such as *Lifecycle Positioning, Data Architecture, Application Domain,* and *Cyber-Physical Security Integration*, the taxonomy provides granularity that is absent in the generic maturity aspects of current frameworks, while maintaining compatibility with global standards [11].

Beyond conceptual clarification, the taxonomy demonstrates practical applicability. Through comparative benchmarking of three diverse use cases – KOEN (generation-oriented), Elvia (operationally focused), and Bentley OpenUtilities (lifecycle-integrated) – the taxonomy reveals that maturity is not absolute, but contextual, shaped by organizational goals, technical architectures, and sectoral priorities. The interactive tool developed alongside the taxonomy operationalizes this framework, offering maturity scores per dimension, radar plots, and benchmarking functionalities. This addresses another gap highlighted in the literature: the scarcity of accessible, practitioner-friendly tools to support evaluation and decision-making [19,13].

The taxonomy thus contributes in three ways: (1) it fills theoretical gaps by extending conceptual coverage of overlooked dimensions; (2) it strengthens methodological rigor through explicit alignment with [11]; and (3) it provides a usable, open-source tool that supports both academic inquiry and practical adoption by utilities, regulators, and technology providers. In addition, its role-specific insights support user experience and interpretability [80], enabling cybersecurity experts to trace threat propagation and mitigation delays, while business analysts can evaluate cost-efficiency and risk trade-offs. In doing so, the taxonomy bridges scholarly discourse and operational practice, establishing a replicable model for reasoning about DT functionalities and maturity in the power grid domain.

6.2. Limitations and future work

While the upgraded taxonomy provides a structured and domain-specific framework for assessing digital twin (DT) maturity in power grids, several limitations remain that point to fruitful avenues for future research and development. First, although the taxonomy enhances conceptual clarity, the current maturity assessment still relies on semi-quantitative judgments. As identified in both the co-occurrence analysis and recent reviews (Y. [7,18], the lack of standardized, quantifiable evaluation metrics limits comparability across systems. In that context, the taxonomy-based maturity assessment relies on pre-defined rules and semi-static logic structures, which, while transparent and reproducible, may not fully capture the nuanced reasoning required in complex, context-sensitive power grid scenarios. For example, interdependencies between dimensions such as cybersecurity integration and lifecycle positioning may vary based on grid topology, regulatory constraints, or emergent threat landscapes. Future enhancements could leverage large language models (LLMs) and agentic AI to incorporate context-aware reasoning [71], dynamically adjusting maturity evaluations based on semantic patterns in technical documentation, system logs, or stakeholder narratives. Such AI-augmented reasoning would enable more

Dimension	Elvia DT	KOEN DT	Bentley OU DT
Data Link	80	80	50
Functional Role	80	80	80
Synchronization Frequency	80	80	80
Intelligence Level	65	65	65
Model Granularity	60	60	60
Data Architecture	70	70	70
Interface Types	67	67	33
Lifecycle Positioning	50	100	50
Application Domain	17	33	50
Cyber Physical Security Integration	33	33	87

Excellent (80-100) Good (60-79) Fair (40-59) Needs Improvement (0-39)

Fig. 8. Heat-map of the comparative benchmarking across DT dimensions for the three use cases.

adaptive, explainable, and situation-specific recommendations, thereby enhancing both the usability and intelligence of digital twin evaluation tools. In addition, operationalizing each dimension with robust indicators can be supported by open datasets, testbeds, and benchmarking protocols aligned with international standards, to further establish this methodology as a standardized approach within the domain. Second, the taxonomy has been validated through selected case studies, but broader application is needed to test its scalability in cross-domain and federated DT architectures. With the increasing integration of DERs, electric vehicles, and demand response mechanisms, DTs will need to coordinate across organizational and jurisdictional boundaries [81]. This calls for research into federated models, multi-agent simulation, and secure data-sharing protocols that extend beyond single-system architectures [67]. In that context, future extensions of the work will focus on partnering with utilities and vendors to gain direct access to system configurations, which will enable deeper validation of our scoring framework and potentially support semi-automated data ingestion for real-time assessments. Third, the analysis revealed that most DT implementations still underperform on cybersecurity and resilience integration. Future studies should explore security-by-design approaches, positioning DTs not only as passive mirrors of system state but also as active defense agents capable of simulating, detecting, and mitigating threats in real time. Alignment with standards such as [87] and [88] can support such an effort. Fourth, the role of human decision-making, interpretability, and ethics remains underexplored. Although the taxonomy facilitates role-specific insights, further research is required to establish frameworks for explainable DT intelligence, human-in-the-loop governance, and operator interaction models that preserve accountability and trust in semi- or fully autonomous systems [80]. Finally, the taxonomy could be extended to policy and market dimensions, reflecting the accelerating role of DTs in carbon accounting, ESG reporting, and cross-border energy trading. Together with the human-in-the-loop governance, this would advance the taxonomy to an Industry 5.0 and Society 5.0 standard (Fonseca i Casas & Pi i Palomes, 2026). Therefore, as a next step we aim to extend our tool to support the tracking of quantitative performance indicators over time (e.g., response time, synchronization lag, frequency of model updates, fault detection latency, and ESG metrics). These are not yet standardized globally, but will be provided in the tool as customizable inputs aligned with operational performance metrics in grid management (e.g., KPIs used in SCADA/EMS environments). Embedding these aspects would enhance the taxonomy's strategic relevance and support its adoption in regulatory and policy contexts.

7. Conclusion

This paper has proposed and demonstrated an upgraded taxonomy for Digital Twins in power grid systems, addressing the limitations of existing generic models and aligning the framework with the unique requirements of the energy domain. By integrating dimensions such as intelligence level, lifecycle positioning, and cyber-physical security, the taxonomy extends beyond traditional maturity models to capture both the technical and organizational complexities of DT deployment in critical infrastructures. The application of the taxonomy to three representative case studies revealed its practical value as both an evaluative and comparative tool. It allowed the differentiation of operationally focused, lifecycle-oriented, and generation-centered twins, highlighting strengths in areas such as real-time synchronization and subsystem granularity, while also exposing persistent gaps in lifecycle integration, cross-domain interoperability, and security-by-design approaches. These insights confirm that DT maturity is inherently contextual, reflecting organizational priorities as much as technical capability.

Beyond its analytical role, the taxonomy provides a foundation for guiding future development of more holistic and resilient DT ecosystems. It offers utilities, technology providers, and regulators a systematic means of benchmarking implementations, identifying weaknesses, and aligning innovation with strategic energy transition objectives. Ultimately, by bridging conceptual clarity and empirical applicability, the taxonomy strengthens the capacity of DTs to serve not merely as mirrors of the grid, but as enablers of intelligent, secure, and sustainable power systems.

CRediT authorship contribution statement

Tanja Pavleska: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process.

During the preparation of this work the author(s) used ChatGPT 5.0 in order to revise and improve the clarity and readability of more technical statements in the paper. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of competing interest

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

Appendix A. . Comparison of digital twin maturity frameworks

Several frameworks have been proposed for assessing the maturity of DTs. Table A1 presents analysis of these frameworks in view of the taxonomy dimensions in order to establish the most suitable one that can be used as the maturity assessment backbone in our tool.

As the analysis show, ISO/IEC 30,186 (2025) stands out as the most comprehensive, addressing all dimensions in some form. It explicitly covers convergence, functional roles, synchronization (time), integration, and trustworthiness, while also providing guidance on lifecycle positioning. DT Consortium Model [18] and OMG DT Assessment Framework [82] provide strong attention to lifecycle and governance, but they remain infrastructure-oriented and are not sufficiently detailed for domain-specific evaluation in energy systems. The SWAN Tool [83] has a clear strength in utility-sector focus but lacks the needed breadth: it does not provide comprehensive lifecycle or cybersecurity coverage, making it less suitable as a general maturity reference. Business-oriented models [84,85],ISO/IEC 33001, 2020) focus heavily on organizational processes, governance, and compliance, but they neglect technical aspects such as synchronization frequency, data link, or intelligence level that are central to DTs in power grids. Finally, academic models (Y. [7]; Z. [21], while offering valuable conceptual clarity and emphasize staged progression and dimension weighting, they remain too abstract or generic, without providing operationalized assessment indicators that practitioners can apply consistently.

Table A1
Comparison of DT maturity assessment frameworks.

Framework	Scope / Strength	Covered Taxonomy Dimension									
		D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
ISO/IEC 30186 (*ISO/IEC 30186*, 2025)	Formal global maturity model, covers all dimensions	√	√	√	√	–	–	–	√	–	√
Digital Twin Consortium Model [18]	Infrastructure-oriented, lifecycle-focused	–	√	–	√	–	√	×	√	×	–
OMG DT Assessment Framework [82]	Lifecycle and sustainability orientation	√	√	√	√	√	√	–	√	×	–
SWAN Tool [83]	Sector-specific, utility-focused	√	√	–	–	√	×	√	×	√	×
Business Maturity Model [84]	Granular business value coverage	–	√	×	×	×	×	×	–	×	×
5–Level Academic Model (Y. [7]	Capability progression stages	√	√	√	√	–	×	×	√	×	–
Generic Evaluation Model (Z. [21]	Dimension weighting across four axes	√	√	√	√	–	×	×	√	×	–
CMMI [85,86]	Process maturity with staged development	√	√	×	√	×	√	√	√	×	–
ISO/IEC 33,001 (*ISO/IEC 33001*, 2020)	Detailed process capability assessment	√	√	×	√	×	√	×	√	×	√

Appendix B. . Correspondence between the taxonomy dimensions and the ISO maturity aspects

Table B1 shows the correspondence between the proposed taxonomy dimensions and the maturity aspects defined in [11]. Each dimension is mapped to the most relevant ISO maturity aspect, with a short rationale explaining the relationship. This provides a systematic bridge between the sector-specific taxonomy and the generic, international maturity model.

The table demonstrates that several taxonomy-dimensions map directly and unambiguously to ISO aspects, for instance, Data Link corresponds to *Convergence*, Functional Role to *Capability*, and Synchronization Frequency to *Time*. At the same time, it also reveals areas of overlapping coverage, where certain dimensions span more than one maturity aspect. For example, Intelligence Level contributes both to Capability, by extending functional scope, and to Convergence, by supporting adaptive alignment with physical systems, while Lifecycle Positioning relates to both *Convergence* and Integrated View. Importantly, the mapping highlights how the taxonomy adds greater granularity and domain-specific detail compared to the more generic ISO model. For instance, Cyber-Physical Security Integration translates ISO's broad *Trustworthiness* aspect into a concrete operational concern for the energy sector, reflecting issues of resilience, integrity, and system safety that are critical for power grids.

Table B1
Correspondence between the taxonomy and ISO 30186 maturity aspects.

Taxonomy Dimension	ISO/IEC 30,186 Maturity Aspect	Rationale
Data Link	Convergence	Strong, continuous data flows ensure alignment between the physical and digital entities.
Functional Role	Capability	Directly reflects what the DT is able to do in terms of functions and outcomes.
Synchronization Frequency	Time	ISO's "time" aspect explicitly evaluates update frequency and latency.
Model Granularity	Integrated View	The granularity defines how detailed and comprehensive the DT is, contributing to system integration.
Intelligence Level	Capability (partially Convergence)	Intelligence extends functional capabilities; adaptability also strengthens convergence with real-world dynamics.
Data Architecture	Integrated View	How data is organized and connected influences the twin's ability to provide an integrated and scalable view.
Interface Types	Capability	Interfaces determine how capabilities are accessed and used by stakeholders or other systems.
Lifecycle Positioning	Convergence & Integrated View	Lifecycle coverage reflects how consistently and broadly the DT integrates data/models across asset stages.
Application Domain	Integrated View	Mapping domain scope shows whether the DT is narrow or spans multiple domains of the grid system.
Cyber-Physical Security Integration	Trustworthiness	Explicitly tied to ISO's trustworthiness aspect: ensuring security, resilience, and safe operation.

Data availability

No data was used for the research described in the article.

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