Digital Twins for Electromagnetic and Energy Transmission Systems: Mathematical Foundations and Simulation Frameworks

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Abstract:
Digital twin technology has emerged as a transformative force in modern engineering. It allows real-time interrelations of physical and virtual resources to be used in the process of monitoring, optimization, and predictive control. This review examines the mathematical foundations and simulation frameworks that support the creation of digital twins, with particular focus on electromagnetic and energy transmission systems. It explores the integration of classical mathematical models that are based on Maxwell equations, finite elements, and model order reduction with modern data-driven and hybrid model strategies to boost accuracy and scalability. The paper also evaluates the progress made in simulation architectures with key features of co-simulation, hardware-in-the-loop testing, and data standards that work together to ensure coordination between the physical and digital worlds. Nevertheless, although there is significant advancement in the accuracy of computing and integration across domains, there are still issues of standardization, cybersecurity, and real-time data assimilation. The paper concludes that to develop digital twins applications in energy and electromagnetic systems, it is important to have unified modeling frameworks, enhanced interoperability protocols, and adaptable algorithms that combine physics-based accuracy with intelligent automation. Such insights lay the basis of future research that would help to come up with resilient, secure, and self-optimizing energy systems.

INTRODUCTION

Research on digital twins for electromagnetic and energy transmission systems has become an important area of study. This is primarily due to the increasing complexity and decentralization of modern power grids, which are influenced by the adoption of renewable energy sources and advancements in power electronics (Song et al., 2023; Ismail et al., 2024). Over the years, the shift from traditional modeling to real-time, data-driven digital twins has allowed for better monitoring, control, and optimization of energy systems (Kantaros et al., 2025; Banerji et al., 2024). This change is crucial for maintaining grid stability, improving operational efficiency, and ensuring resilience amid increasing uncertainties and changing load patterns (Zomerdijk et al., 2024; Mchirgui et al., 2024). With global energy demand expected to rise by 50% by 2050, this situation underscores the need to rapidly deploy advanced digital tools that can effectively manage the complex and overloaded transmission and distribution networks (Ismail et al., 2024; Imam, 2025).

The growing complexity of modern electromagnetic and energy systems has renewed the need for better modeling and predictive tools that can help ensure reliability, efficiency, and resilience. The idea of Digital Twin (DT) has come up as a game-changing approach. It allows for the creation and use of a virtual version of physical assets, systems, or processes. This virtual model continuously reflects its real-world counterparts through data exchange and computational modeling (Tao et al., 2019). Imandi et al. (2025a) argue that digital twins offer a unique capability by consistently integrating data from sensors, simulation models, and

operational feedback. This ongoing data blending allows for real-time monitoring, predictive maintenance, and performance improvement across various engineering fields.

The Digital Twin concept represents a significant shift from conventional simulation models to highly synchronized, predictive virtual representations. A DT is officially described as a collection of virtual information constructs that replicate the structure, context, and behavior of a physical system or systems of systems (National Academies of Sciences, Engineering, and Medicine, 2024, p. 6). At the core of this description is the bi-directional interaction between the virtual and physical realms, facilitated by ongoing, dynamic updates that utilize real-time sensor data from the physical twin. This functionality allows the DT to have predictive capabilities and support critical decisions that create value for the physical system throughout its lifecycle.

The advancement of effective digital twin (DT) implementation has been fundamentally influenced by the integration of cutting-edge technologies. This includes the swift growth of the Internet of Things (IoT), a system of interconnected devices that contain sensors and software, which enables seamless data flow (Ma et al., 2024). Alongside the capacity to oversee and interpret large datasets (Big Data analytics), enhanced computing capabilities, and the use of advanced artificial intelligence (AI) and machine learning (ML) techniques, these resources facilitate the collection and automated processing of extensive operational data (Cioara et al., 2023). This integration streamlines the data analysis workflow, allowing the digital representation to accurately confirm the condition of real-world assets and derive valuable insights essential for predictive optimization.

A key distinction in the digital twin life cycle is made between the prototype and the instance. The Digital Twin Prototype (DTP) is developed and improved during the design phase, going through various tests before the physical version is produced (Iliuţă et al., 2024). Once finalized and validated, the physical model is created. Each physical unit based on that design then has its own Digital Twin Instance (DTI). The DTI begins during the production phase and is directly linked to its physical counterpart throughout its specific life span. Data from the real world is continuously sent to the digital space, while information is also relayed back to anticipate and monitor the system's performance. This conceptual framework is crucial for overseeing the life cycle of high-voltage power equipment.

The Digital Twin (DT), a concept originating from aerospace and advanced manufacturing, offers a compelling solution. A DT is more than a high-fidelity simulation; it is a live, bi-directionally linked virtual model that continuously synchronizes with its physical counterpart, allowing for real-time condition monitoring, predictive maintenance, fault diagnosis, and sophisticated "what-if" scenario planning that is impossible to perform on the live grid. The objective of this paper is to examine the existing literature regarding the topic to provide a comprehensive understanding and appreciation of theoretical underpinnings, modeling techniques, and simulation architectures that enable accurate and efficient digital representations of energy transmission systems.

MATHEMATICAL FOUNDATIONS FOR CAPTURING ELECTROMAGNETIC PHENOMENA IN DIGITAL TWIN FRAMEWORKS

The development of high-fidelity Digital Twins (DTs) of electromagnetic (EM) and energy transmission systems requires the adoption of mathematically sound modeling techniques that can no longer neglect the complex EM field behavior over large temporal and spatial scales. These foundational approaches need to provide a balance between the quality of the simulation (fidelity) and the computational cost (scalability), especially when applied in the process of real-time decision-making loops.

The cornerstone of precise EM DT modeling lies in established numerical methods, primarily derived from solving Maxwell's equations given as.

$$\nabla \times \mathbf{E} = i\omega\mu\mathbf{H}, \quad \nabla \times \mathbf{H} = -i\omega\varepsilon\mathbf{E} + \mathbf{J}$$

These equations are basic examples of how the principle of electromagnetic induction works, wherein a time-varying electric field produces a solenoidal magnetic field, and a time-varying magnetic field induces a circulating electric field. It is this synergistic and self-perpetuating interaction between the magnetic and electric fields that is the key to the propagation of electromagnetic waves/light and radio waves through free space as well as material media.

The rigorous applications of Maxwell equations in Digital Twin (DT) models assume the distinction of time-domain and frequency-domain solutions, and the decision is made based on the operational need. The frequency-domain analysis, which commonly applies the time-harmonic equations, is effective in studying steady-state processes like the continuous wave propagation, thermal equilibrium analysis, and the calculation of component-level fields at the frequency of operation of the grid, or at frequencies used in communication. This approach is ideal for optimization and continuous monitoring of static conditions (Oliveri et al., 2022; Serteller & Üstündağ, 2008). On the other hand, time-domain solutions are necessary to record high-fidelity transient events and dynamic behavior, such as switching surges, fault propagation, lightning strike, and non-linear response of power electronics to the grid. Such time-dependent simulations play a crucial role in the predictive capabilities of the DT in terms of the resilience and stability of the system since they are able to effectively model the change in fields over time, something that the frequency-domain approach cannot do in its entirety (Khattak et al., 2023; Vuong and Dinh, 2020). Thus, a full DT architecture would need to include both techniques with the computationally intensive time-domain models (often offline), generating training information which is then used in online reduced-order models (ROMs) to obtain faster and more efficient results.

Finite-Difference Time-Domain (FDTD) is one of the most important computational methods to simulate the rapid dynamics of transient electromagnetic questions with a high level of accuracy (Imandi et al., 2025b). FDTD is a direct solution to the coupled time-dependent curled Maxwell equations where both time and space are discretized with the staggered grid (Yee, 1966). It is so suitable in modeling broadband electromagnetic waves, and in the modeling of highly non-linear, time-varying interactions, such as those caused by high-frequency noise or impulsive events like lightning over voltages in transmission systems, that its explicit, step-by-step nature places it extraordinarily well-suited. Although the FDTD method is conceptually simple and quite accurate, the main limitation, which is common to other full-wave solvers such as the FEM is its large computational cost, due to the fact that both the spatial grid size and the time step size have to be limited by stability. In a real-time DT system, therefore, FDTD is mainly applied in a simulation (offline) mode of high-fidelity component design verification and the production of physically realistic datasets that can be used to train computationally efficient Artificial Intelligence (AI) and Machine Learning (ML) surrogate models (Chen & Hoefer, 2024).

In addition, the Finite Element Method (FEM) is also extensively used due to its capability to accommodate complex geometries and material nonlinearities having aided it to be indispensable in modeling components such as power transformers, non-destructive testing (NDT) systems and high-frequency appliances (Palanisamy and Lord, 2003; Serteller and Ustundag, 2008). FEM is powerful because it has a high spatial resolution and fidelity in the representation of magnetostatic and magneto-dynamic problems (Vuong & Dinh, 2020). This high fidelity, however, comes at a high price: FEM is expensive to meshing and systems of equations, and thus, can be computationally extremely expensive to the point that it is impractical to use in real-time DT simulations.

Other methods that can be used as a foundation are the Method of Weighted Residuals (MWR), which provides a more general mathematical approach to the formulation and solution of field problems (Chen & Hoefer, 2024), and the Partial Element Equivalent Circuit (PEEC) method. PEEC has been shown to be useful

in modeling EM phenomena in terms of equivalent circuit representations, potentially computationally efficient to electrical systems by exploiting the existing circuit analysis tools (Khattak et al., 2023). Most importantly, these full-wave techniques deliver the gold standard in accuracy but due to their computationally intense nature, require the application of auxiliary techniques to be used in DT.

For DT's modeling of the wireless communication environment, where wave propagation over large domains is the primary concern, high-frequency approximations often supersede full-wave CEM methods. Ray-launching models are highlighted as essential methodologies for facilitating the examination of electromagnetic propagation in real-time wireless networks (Zhu et al., 2024a; Zhu et al., 2024b). Ray-launching methods offer vastly superior speed and scalability for large urban or complex indoor scenarios compared to the fine-grained discretization required by FEM. This high efficiency makes them ideal for the real-time performance demanded by the communication network of DTs.

A critical critique that is, however, needed is that ray-based models are based on geometric optics and diffraction approximations. They are inherently less accurate near resonant structures, complex material boundaries, or in scenarios dominated by low-frequency induction, making them unsuitable for component-level DTs that require precise field distribution (e.g., within a transformer core). Therefore, the choice between FEM and ray launching involves a fundamental trade-off between precision (FEM) and computational speed (ray launching), dictated by the specific application's scale and frequency regime.

In order to resolve the problem of high fidelity and real-time performance, Model Order Reduction (MOR) methods are necessary in practice when implementing DT. Dimensionality reduction techniques, such as Proper Orthogonal Decomposition (POD), make it possible to quickly parameterize and run complex full-wave models in the DT environment (Khattak et al., 2023; Zorzetto et al., 2025). POD allows a sort of hybrid modeling, where the complicated model is created offline, and the reduced-order model is employed to create fast, dynamic predictions online, thus avoiding the real-time constraints of the original high-fidelity FEM solution.

Beyond efficiency, new paradigms address specific modeling challenges. In combination with CEM, nonlinear inverse scattering approaches provide a robust solution to forecast such properties as the Radar Cross Section (RCS) of any target which is a specialized feature of the problem that is hard to effectively predict using traditional forward solvers (Alqadah & Ziegler, 2024). Moreover, the algebraic topological approach is also receiving commendation as an alternative to modeling using differential equations. This approach aims to provide a more straightforward and computationally efficient way to solve EM problems, which may enhance the computational effectiveness of the method by eliminating the need for complex meshing and matrix inversion that is part of FEM through the use of physically measurable scalar quantities (Bhatt & Sankaran, 2019).

For DTs of complex energy systems, such as transformers, a single EM model is insufficient; multiphysics coupling is required for true operational fidelity. The most accurate DTs integrate magnetic field modeling with thermal-airflow field modeling, typically using a magnetic-thermal one-way coupling analysis (Yuanqi et al., 2023). This necessity introduces significant computational complexity, which is managed through multi-level modeling utilizing techniques like aggregation and de-aggregation (Yuanqi et al., 2023). These methods let the DT put computational resources where they are most needed and abstract less important parts. This makes the overall simulation more accurate without crashing under the weight of a fully coupled, high-resolution model. This highlights that the ultimate appraisal of a mathematical modeling technique in the DT context must include its ability to integrate seamlessly with other physics domains to produce a complete, predictive digital representation.

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly employed to develop surrogate models that precisely replicate the input-output dynamics of intricate physical simulations while markedly enhancing computational efficiency (Khan et al., 2023). These computationally efficient surrogates are

essential for optimization, sensitivity analysis, and uncertainty quantification in the DT framework for hybrid and sustainable energy systems (Khan et al., 2023).

Physics-Informed Machine Learning (PIML) is a big step forward in this field because it puts physical laws that are specific to the field directly into the learning process. PIML doesn't just use real-world data; it also adds the governing equations, which are usually written as partial or differential-algebraic equations, to the neural network's architecture or loss function. This feature makes sure that the models that come out of it are still physically consistent (Kuang et al., 2024). This combination of data and physics creates models that are both understandable and useful in a wide range of situations, which solves the main problems with methods that only use data (Hunde et al., 2025).

In this context, Physics-Informed Neural Networks (PINNs) have become a very useful way to combine data-driven learning with basic physics principles. PINNs direct network training toward solutions that comply with fundamental physical laws by incorporating physical constraints into tailored loss functions (Yang et al., 2024). For electromagnetic digital twins, PINNs use Maxwell's equations as soft constraints. This lets the network learn physically valid field distributions while also capturing complex or unmodeled phenomena from data (Chen & Dal Negro, 2022; Nohra & Dufour, 2024).

This method has been demonstrated to improve generalization to novel situations and resilience to noisy data, in contrast to conventional data-driven models, which is a crucial feature for digital twins functioning in dynamic or uncertain environments (Wong et al., 2021). The incorporation of AI surrogates into physics-integrated operational architectures facilitates real-time performance optimization and hidden state inference, enabling digital twins to attain both precision and adaptability in dynamic environments (Farhat & Altarawneh, 2025).

INFLUENCING FACTORS IN THE SELECTION OF MATHEMATICAL MODELING TECHNIQUES FOR EM DIGITAL TWINS

The choice of mathematical modeling techniques for developing Digital Twins (DTs) focused on electromagnetic (EM) phenomena is a complex decision. It involves balancing fidelity, speed, and deployment feasibility. This selection process affects the DT's trustworthiness, efficiency, and usefulness throughout the asset's lifecycle (Antil, 2024a; San et al., 2021). The influencing factors can be grouped into three related categories: the demands of the physical system, constraints imposed by computational efficiency, and requirements for architectural integration.

The main influence comes from the specific system context and application needs. The physical system's nature determines the required resolution and complexity. This can mean models that handle multi-scale and multi-physics issues when needed, such as combining EM analysis with thermal dynamics (Antil, 2024b). The required end-use metrics, whether focusing on manufacturing quality, reliability, or performance optimization, also dictate the necessary model accuracy and ability to assess uncertainty reliably (Li et al., 2021). For example, modeling the EM environment requires considering factors like wireless link setups and diffuse scattering, which directly affect the choice between quick but approximate Ray Launching models and heavier full-wave techniques (Zhu et al., 2024).

The second major influence is defined by computational efficiency and accuracy constraints. A major challenge is scalability; the selected model must run fast enough for real-time use while maintaining sufficient accuracy (Kantaros et al., 2025). This need for efficiency often steers the modeling choice toward methods designed for speed (San et al., 2021). As a result, the decision heavily relies on the ability to effectively use surrogate models or Reduced Order Models (ROMs). The selected model must be capable of generating reliable training data, while establishing effective training strategies and evaluating the reliability of the surrogate models is essential (Oliveri et al., 2022). The aim is to accurately represent key observables like scattering matrix entries without incurring the high costs of continuous high-resolution simulation (Oliveri et al., 2022).

Lastly, the growing complexity of DTs imposes limitations related to data integrity and integration. The model should not create major interoperability issues and must work well with advanced software systems and computational tools (Kantaros et al., 2025). This often leads to hybrid modeling strategies that easily integrate with modern Machine Learning (ML) algorithms and support seamless interface learning and multifidelity coupling across different physics and scales (San et al., 2021; Li et al., 2021). Furthermore, the chosen model must promote data governance by ensuring reliability and adequately addressing measurement uncertainties throughout the DT's lifecycle (Antil, 2024c).

The decision on which mathematical modeling technique to use involves finding the right balance among physical accuracy, computational speed, and compatibility with broader DT data and control architectures.

Mathematical Modeling of Energy Transmission Systems
Localized electromagnetic field analysis follows Maxwell's equations, but creating a complete digital twin (DT) for an energy transmission system requires a set of mathematical models that capture the overall operational behavior, stability, and control of the entire power network (Song et al., 2023). These system-level models establish the electrical state of the twin and are typically linked to high-fidelity electromagnetic models through co-simulation frameworks and layered architectures (Addo et al., 2025).

Differential-Algebraic Equations (DAEs) for System Dynamics
The basic mathematical structure for analyzing the dynamic behavior and stability of power systems is the system of Differential Algebraic Equations (DAEs) (Groß et al., 2016; Wang, 2015). This combined framework is key to the digital twin's predictive abilities, especially for rapid changes and disturbances. The system consists of two types of equations: Differential Equations that reflect the dynamic characteristics of energy conversion equipment like generators and turbines, along with related control and protection systems (governors, exciters). While rotor dynamics are governed by second-order swing equations, they are usually rewritten as first-order differential equations by defining angular speed as a state variable (Sauer & Pai, 1997). These equations describe how state variables such as rotor angle, speed, and voltage change over time. Complementing these are Algebraic Equations, which show the steady-state constraints of the network, enforcing Kirchhoff's laws and power balance at all buses and nodes while linking the voltage and current magnitude and phase across the network setup (Milano, 2016). Solving these DAE systems, typically using implicit integration methods, allows the digital twin to conduct crucial analyses like transient stability and voltage stability assessments, which are often needed in faster than real-time (FTRT) environments for operational support (Liu & Sun, 2019).

Component-Level Network Models
The overall DAE system is based on simplified yet reliable equivalent circuit models of individual physical assets. These models represent the electrical features of components while simplifying the complex internal field physics (Aboubi et al., 2024). Transmission lines are usually represented with lumped parameter models, like the π model, which includes series impedance (resistance and inductance) and shunt admittance (capacitance); distributed parameter models are used for accurately modeling wave travel and high-frequency effects over long distances (Colon Reyes et al., 2023). Transformers are modeled through equivalent circuits that consider leakage inductance, winding resistance, and magnetizing reactance, often factoring in tap changer dynamics; for high fidelity analysis, the digital twin must account for the magnetic non-linearity of the core material to accurately simulate saturation and inrush current (Wang et al., 2024). Additionally, properly representing system loads is crucial for stability, as they are modeled dynamically based on their dependence on voltage and frequency, often using ZIP models (constant impedance, current, and power components) to reflect realistic consumer behavior and its impact on grid stability (Colón Reyes et al., 2024). Moreover, the rising presence of renewables requires detailed models for power electronics (inverters), whether grid-following or grid-forming. These are represented through complex control loop models that introduce rapid, non-linear dynamics into the DAE system, needing specialized stability tools and faster processing within the digital twin (Hwang et al., 2025).

SIMULATION FRAMEWORKS AND ARCHITECTURES FOR DIGITAL TWIN OPERATION

The effectiveness of a Digital Twin (DT) in electromagnetic (EM) and energy transmission systems depends on the simulation framework, which is the computational platform that runs the mathematical models, integrates real-time data, and allows for the bidirectional interaction with the physical asset. To handle the varied demands of EM systems, these frameworks are usually organized around the need for real-time synchronization, managing multi-domain complexity, and validating hardware.

REAL-TIME EXECUTION AND PERFORMANCE CONSTRAINTS

A key requirement for any operational DT is real-time execution, ensuring the virtual model evolves in sync with the physical system. This is done through Faster-than-Real-Time (FTRT) simulation platforms, which often use specialized hardware like Field-Programmable Gate Arrays (FPGAs) to greatly speed up computational models (OPAL-RT, 2020). Platforms designed for Cyber-Physical Power Systems (CPPSs), such as ECS-Grid, showcase the use of data-oriented, entity-component-system (ECS) structures to enable highly scalable electromagnetic transient analysis at these faster speeds (Huang et al., 2023).

However, achieving FTRT speed comes with a trade-off in model fidelity. The highly complex, full-wave mathematical models (like high-resolution FEM) mentioned earlier must undergo Model Order Reduction (MOR) to meet strict time requirements. As a result, the real-time operational model is often just an approximation of the original design model, which limits the fidelity that can be maintained during dynamic operation.

CO-SIMULATION FOR MULTI-DOMAIN SYSTEM COMPLEXITY

Modern energy and EM assets seldom operate in isolation; they function as complex systems-of-systems involving interconnected physics domains (electrical, thermal, mechanical, and communications). To capture this complexity, DT implementation favors co-simulation architectures over single solvers (Palensky, 2024). Co-simulation achieves system-level accuracy by breaking the overall problem into specialized sub-models, each solved by the most suitable domain-specific simulation tool. Middleware platforms, such as HELICS or Mosaik, are used to manage time synchronization, data exchange, and communication protocols between these separate simulators (POLITECNICO DI TORINO, 2024). This method offers significant benefits in scalability by spreading the computational load across various nodes. Additionally, it is crucial for advanced DT functions, such as integrating power flow simulators, climate forecast models, and AI-based controllers in complex grid operations (Addo et al., 2025). Co-simulation's ability to connect these different elements from low-level EM fields to high-level market controls is vital for creating a comprehensive DT ecosystem.

HARDWARE-IN-THE-LOOP VALIDATION

The Simulation Framework must include a method for verifying the performance of actual embedded control systems that manage the physical asset. This is called Hardware-in-the-Loop (HIL) testing, which uses the DT model as a virtual representation of the plant.

In an HIL setup, the real-time DT model operates on an FTRT platform and is electrically linked to the physical controller (like a protection relay or power electronics ECU). This closed-loop setup ensures that the controller is tested with realistic sensor inputs created by the simulation, and its outputs (actuator commands) feedback to drive the virtual plant model. This method is more effective than purely software-based testing as it validates the controller's ability, its implementation delay, and the physical interaction of its I/O components, which are crucial for safety-critical EM and power systems (Balan et al., 2025). Ultimately, HIL systems lower development risks by allowing engineers to safely test dangerous or system-critical "what-if" scenarios on a virtual asset (OPAL-RT, 2020).

DISTRIBUTED DEPLOYMENT ARCHITECTURE

The data velocity and computational volume associated with operational DTs demand a distributed deployment strategy. This involves contrasting roles for centralized and decentralized computing resources (IEC, 2024). Cloud platforms typically host the aggregated DT data (Digital Twin Aggregates), providing the elastic resources necessary for long-term planning, historical trend analysis, and the training of deep learning models used for prediction.

In contrast, to meet the sub-millisecond latency requirements of control and protection, lightweight DT models or specific intelligent agents are deployed at the edge (AIOTI WG Energy, 2024). These Edge frameworks ensure that immediate monitoring and prescriptive control actions can be executed rapidly, reducing reliance on centralized connectivity. The integration of these distributed frameworks hinges on a robust Data Platform that maintains continuous, secure, and bidirectional synchronization, ensuring the digital and physical states remain coherent throughout the system's operational lifecycle (Rolofs et al., 2024).

INTEGRATED AND HYBRID MODELING STRATEGIES FOR OVERCOMING DIGITAL TWIN SCALABILITY ISSUES

The inherent complexity, large data needs, and real-time requirements of industrial systems often create significant scalability challenges for Digital Twin (DT) applications. To address these challenges, which involve computational speed, data management, and architectural coordination, a systematic approach that combines various modeling strategies is needed instead of relying on a single, unified solver. This approach primarily focuses on blending physics-based knowledge with data-driven intelligence and creating multi-level data architectures.

ENHANCING COMPUTATIONAL EFFICIENCY THROUGH HYBRID AND MULTI-FIDELITY MODELING

The most direct way to improve scalability is through Hybrid Modeling Strategies, which merge physics-based simulations with data-driven algorithms (Wang et al., 2022). This method is essential because purely physics-based models are too costly in terms of computation for real-time operation, while purely data-driven models lack the generalization capability and physical limits needed for effective industrial use (San et al., 2021). The hybrid model greatly improves prediction accuracy and adaptability, enabling ongoing real-time monitoring and fault diagnosis, which is vital for operational efficiency in asset-heavy industries.

Complementing this, Multifidelity Computing is crucial for optimizing the utilization of modeling resources. By employing multifidelity coupling approaches, a DT can efficiently transfer information across different scales and physics, leveraging accurate but sparse high-fidelity models alongside abundant, lower-cost data or low-fidelity models (San et al., 2021). This integration strategy enhances the model's generalizability and ultimately reduces the computational burden associated with acquiring high-fidelity results across the entire operational envelope. Furthermore, this integration is vital for the creation of reduced-order models (ROMs) that are necessary for high-speed execution; techniques like Machine Learning and Artificial Intelligence (AI) are specifically employed to train these ROMs, significantly boosting computational efficiency over traditional, resource-intensive multiphysics methods (Catelani, 2021). An adaptive framework utilizing an ensemble of surrogate models can further enhance this efficiency by providing robust approximations while dynamically selecting the optimal model based on current system factors, thereby reducing computational costs and improving performance (Lai et al., 2023).

ARCHITECTURAL AND DATA SCALABILITY

Beyond computational efficiency, integrated modeling strategies address the scalability of the DT's architecture and its data management capabilities. The integration of various modeling strategies, including physics-informed simulations and hybrid machine learning, facilitates data unification and improves interoperability, leading to more adaptable virtual models (Kantaros et al., 2025). This capability is vital for managing data heterogeneity and quality assurance across diverse data streams, enabling efficient data fusion and robust, adaptable DT deployments (Ouedraogo et al., 2025).

At an architectural level, integration supports the scaling of complex systems through hierarchical aggregation. The concept of a Type DT Aggregate, which groups Digital Twin Instances (DTIs) of the same type, is one such mechanism (Van Bruggen et al., 2023). This approach simplifies the complexity of managing and implementing unique machine learning workflows across a multitude of individual DTs. Similarly, the Democratized Learning (Dem-AI) scheme facilitates scalable multi-level hierarchical data integration from distributed DTs, effectively merging diverse data while maintaining cohesive relationships between specialized and generalized models (Picano et al., 2024). Harmonizing lifecycle data, clarifying dependencies,

and streamlining data pipelines through multi-model integration further reduces the development and maintenance effort, which is a key component of long-term scalability (Malakuti et al., 2021; Zhang & Li, 2024).

ORCHESTRATION AND AUTOMATION FOR LIFECYCLE SCALING

Finally, integrating various modeling strategies enhances the scalability of the entire DT lifecycle and operational response. AI techniques like machine learning and neural networks enhance data processing capabilities and interoperability, simplifying the management of complex data workflows across diverse industrial domains (Hao et al., 2024). This orchestration capability is formally managed through systems like the Behavior Execution Framework (BEFDIT), which coordinates heterogeneous simulations, supports co-simulation, and enables dynamic resource allocation, ultimately improving the scalability of decision support for complex applications (Bellini et al., 2025).

Furthermore, the integration of Generative AI (e.g., 2D-to-3D models and Large Language Models) offers a new paradigm for streamlining the DT development process itself (Gebreab et al., 2024). By automating key stages of modeling and data integration, Generative AI addresses the scalability challenge inherent in manually configuring and synchronizing the diverse data sources required for large-scale DT creation. Integrating simulation models for real-time decision-making and what-if analysis further enhances scalability by allowing operators to effectively adapt to the increasing complexity and variability of modern manufacturing and energy systems (Abdoune et al., 2023).

CONCLUSION

Digital Twins (DTs) have arisen as a revolutionary method in electromagnetic and energy transmission systems, connecting physical assets with virtual models to facilitate real-time monitoring, predictive analysis, and operational enhancement. Improving accuracy and computational efficiency through the combination of classical mathematical models, such as Maxwell equations, finite elements and differential-algebraic equations, with modern data-driven and hybrid approaches enhances the modelling and analysis of the accurate solutions. Co-simulation, hardware-in-the-loop testing, and multi-fidelity modeling simulation frameworks are important to attain real-time multi-domain performance. Despite massive progress, challenges still exist in areas such as standardization, cybersecurity, model interoperability, and real-time scalability. Physics-informed machine learning and surrogate modeling present viable solutions to address computational limitations while maintaining physical accuracy. In addition, distributed architectures and edge computing as well as generative AI are emerging as critical enablers to large, flexible digital twin systems. The development of energy and electromagnetic systems digital twins requires unified modeling guidelines, stronger interoperability policies and a computational combined strategy that blends physics-based precision with smart automation. The challenges that are going to be confronted will facilitate the design of strong, safe, and self-optimizing energy infrastructures that may meet the dynamic demands of modern power systems.

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