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A Digital-Twin Architecture for Real-Time DER Coordination Using Graph Neural Networks, State Estimation, and Uncertainty-Aware Dispatch

Thomas Jensen^{1*}, Mikkel Hansen¹

Abstract

Real-time coordination of distributed energy resources is increasingly complex because distribution grids now operate with high variability, bidirectional power flows, and rapidly changing local constraints. Digital twins, graph neural networks, state estimation, and uncertainty-aware dispatch provide complementary capabilities for managing this complexity. This article proposes a layered digital-twin architecture that combines state estimation, graph neural network analytics, and uncertainty-aware dispatch for real-time DER coordination. The objective is to describe an architecture that is conceptual, modular, and suitable for active distribution network operation. The architecture is designed conceptually, with layers for physical grid mirroring, measurement fusion, topology-aware learning, and robust dispatch. A validation strategy is positioned as a future pathway rather than as an experimental contribution. The proposed architecture modularizes the DER coordination task into interoperable layers with distinct responsibilities and interfaces. Three tables are used to define the architecture layers, applicable GNN functions, and uncertainty-handling mechanisms. The architecture provides a blueprint for next-generation distribution management systems that require real-time observability, learning-based analytics, and robust decision support. It is intended to guide future implementation, simulation, and field validation.

Keywords Digital twin, DER coordination, Graph neural networks, State estimation, Uncertainty-aware dispatch, Architecture

*Correspondence:

Thomas Jensen
thomas.jensen@gmail.com

¹ Department of Sustainable Energy Networks, Faculty of Engineering, Technical University of Denmark, Lyngby, Denmark

Introduction

Real-time DER coordination in active distribution networks requires architectures that can represent the physical grid, assimilate heterogeneous measurements, and support rapid operational decisions under uncertainty. Digital twins have been proposed as synchronized digital representations of power systems, where operational data, asset models, and analytical services are organized into a continuously updated cyber-physical environment [1]. In this article, the digital twin is treated not as a single software object but as a layered coordination architecture that connects grid sensing, state estimation, GNN analytics, and dispatch. The central contribution is a conceptual design that clarifies how these layers could interact without presenting experimental results.

Digital twins for future power systems are expected to support monitoring, diagnostics, planning, and control by maintaining a structured relationship between physical assets and digital models [2]. For DER coordination, this relationship is especially important because local photovoltaic generation, storage, flexible loads, and electric vehicle

charging can change network states faster than traditional planning-oriented tools can capture. A digital-twin architecture designed for DER coordination would therefore need synchronization mechanisms, topology-aware analytics, and decision interfaces that can operate close to real time [3]. The architecture proposed here uses these requirements to organize the coordination task into separable but interoperable layers.

Graph neural networks provide a natural analytical foundation for this architecture because distribution grids are graph-structured systems with buses, lines, switches, transformers, and controllable DER devices. Reviews of GNN applications in power systems show that graph convolution, attention, and message-passing models can support state estimation, voltage prediction, topology inference, and other grid analytics [4]. In the proposed architecture, GNNs are not used as isolated predictive models but as an analytics layer that consumes state-estimated grid representations and produces topology-aware indicators for dispatch. This positioning allows the architecture to combine physical modeling, data-driven learning, and operational decision support.

State estimation remains essential because the digital twin must operate on a consistent representation of the grid rather than on raw measurements alone. Data-driven and physics-aware approaches to distribution system state estimation demonstrate how measurements, network equations, and learning models can be combined to improve observability in low-instrumented distribution systems [5]. The architecture therefore places state estimation before GNN analytics so that learned representations are grounded in a coherent operational state. Uncertainty-aware dispatch is then used to convert estimated and predicted conditions into robust DER coordination actions.

DER Coordination Problem

Real-time operational challenges

The real-time DER coordination problem arises because distribution networks increasingly contain controllable resources whose behavior affects voltage profiles, line loading, losses, and local congestion. Network-aware DER aggregation frameworks show that flexibility must be coordinated with awareness of feeder constraints rather than treated as a purely market-side resource [6]. In the proposed architecture, DER coordination is framed as an operational problem in which dispatch decisions must respect the current feeder state and anticipated near-term changes. This makes the digital twin a coordination environment rather than only a visualization or monitoring layer.

Data and topology complexity

DER coordination depends on data from smart meters, feeder sensors, inverters, protection devices, weather services, and distribution management systems, but these data streams differ in latency, quality, and spatial resolution. Multi-source state estimation research highlights that PMU, SCADA, AMI, and other measurements can provide complementary observability when fused through suitable estimation methods [7]. At the same time, topology changes caused by switching, outages, maintenance, or reconfiguration can alter the meaning of those measurements. The architecture therefore treats topology as a first-class data object that must be synchronized with the physical grid and exposed to downstream analytics.

The role of uncertainty

Uncertainty enters DER coordination through renewable generation variability, load forecasting error, incomplete sensing, communication delay, and model mismatch. Distributionally robust and chance-constrained dispatch studies demonstrate that uncertainty-aware formulations can protect operational feasibility when forecasts and system conditions are imperfect [8]. In this architecture, uncertainty is not deferred to a final optimization block but is propagated from measurement fusion through GNN analytics into dispatch. This design would be expected to make coordination decisions more resilient to uncertain grid states and DER availability.

Digital Twin Requirements

Mirroring and synchronization

A digital twin for DER coordination must mirror the physical distribution grid at multiple levels, including assets, topology, measurements, operating states, and controllable devices. Power-system digital twin reviews emphasize the need for data federation, synchronization, and lifecycle consistency across heterogeneous cyber-physical resources [9]. In the proposed architecture, mirroring is implemented as a continuous alignment between field data and digital models rather than as a static network database. Synchronization must also support event-driven updates when switches, DER setpoints, or measurement streams change.

Analytical capabilities

The architecture requires analytical capabilities that go beyond conventional monitoring because DER coordination depends on anticipating voltage, congestion, and flexibility conditions. Physics-informed graph neural networks for state estimation and grid learning indicate that graph-based models can embed network structure while learning from operational data [10]. These capabilities are positioned in a GNN analytics layer that receives estimated states and topology objects from the digital twin. The analytical layer is therefore designed to produce decision-relevant signals rather than independent predictions detached from operations.

Real-time decision support

Real-time decision support requires the architecture to convert the estimated and predicted grid condition into DER setpoints, flexibility requests, or operating envelopes. Online model-free DER dispatch methods suggest that adaptive sensitivity estimation and chance-constrained programming can support voltage-aware operational decisions without relying entirely on fixed models [11]. In the proposed architecture, the dispatch layer would use state estimates, GNN forecasts, and uncertainty descriptors to generate robust control recommendations. Human operators remain part of the decision loop through override, audit, and approval interfaces.

Proposed Architecture

High-level layered design

The proposed digital twin is organized into four functional layers: the physical grid layer, the state estimation layer, the GNN analytics layer, and the uncertainty-aware dispatch layer. Layered smart-grid digital twin concepts support this separation because synchronization, analytics, and control functions have different data requirements and update rates [12]. The physical grid layer mirrors assets and telemetry, the state estimation layer produces a coherent operating state, the GNN analytics layer extracts topology-aware predictions, and the dispatch layer recommends DER actions. This high-level design is intended to be modular enough for gradual deployment in existing distribution management environments.

Figure 1 presents the proposed layered digital-twin architecture, showing how synchronized grid mirroring, state estimation, graph neural network analytics, and uncertainty-aware dispatch interact to support real-time DER coordination.

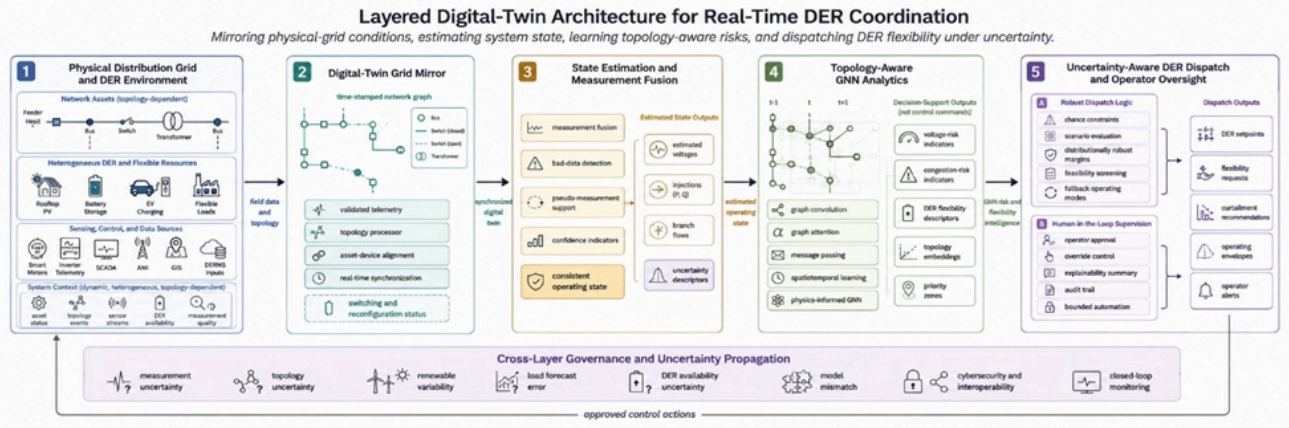


Figure 1. Layered Digital-Twin Architecture for Real-Time DER Coordination under Topology and Uncertainty Constraints

Data flow and interfaces

Data flow begins with physical measurements and asset updates, which are normalized into a grid model and passed to the state estimation layer. Bayesian information fusion approaches for distribution state estimation show how uncertain measurements can be combined into a probabilistic view of the system state [13]. The estimated state then becomes the structured input for GNN analytics, where bus, branch, and DER features are represented as graph attributes. Dispatch receives state estimates, GNN outputs, uncertainty descriptors, and operational constraints through defined interfaces so that each layer can evolve without breaking the entire architecture.

Scalability and modularity

Scalability is addressed by allowing feeder-level digital twins to operate as local modules while exchanging boundary conditions with neighboring feeders, substations, or regional control systems. Graph-based distribution state estimators suggest that network locality can be exploited because many operational dependencies follow feeder topology and electrical distance [14]. Modularity is also necessary because utilities may deploy sensing, estimation, GNN analytics, and dispatch functions at different maturity levels. The architecture therefore separates core responsibilities while preserving a common information model across layers.

Integration with existing systems

The architecture is designed to integrate with existing SCADA, AMI, distribution management, DER management, and outage management systems through service interfaces rather than wholesale replacement. Digital-twin work on integrated energy scheduling shows that twin-based coordination can link operational models with renewable and load uncertainty in a scheduling environment [15]. In this article, integration is conceptualized as a set of data and control gateways that allow the digital twin to ingest measurements, publish estimated states, receive DER availability, and return dispatch recommendations. Table 1 summarizes the architecture layers, their responsibilities, inputs and outputs, and enabling technologies.

Table 1. Overview of the Digital-Twin Architecture Layers

Architecture layer	Primary function	Main inputs	Main outputs	Key technologies and interfaces
Physical grid layer	Maintains a synchronized mirror of assets, topology,	Feeder models, switch states, sensor streams, smart-meter data,	Time-stamped network graph, validated	SCADA, AMI, DERMS, GIS, topology

	measurements, and controllable DER devices	inverter telemetry, DER availability	telemetry, topology events, asset status	processor, telemetry gateway
State estimation layer	Fuses heterogeneous measurements into a coherent operational state with uncertainty descriptors	Network graph, pseudo- measurements, real- time measurements, topology status, measurement quality flags	Estimated voltages, injections, branch flows, confidence indicators, bad-data flags	Weighted least squares, Bayesian estimation, robust estimation, measurement validation
GNN analytics layer	Learns topology-aware representations and predicts operational risks relevant to DER coordination	Estimated state, graph topology, DER attributes, historical operating patterns, uncertainty features	Voltage-risk indicators, congestion-risk indicators, topology embeddings, DER flexibility descriptors	Graph convolutional networks, graph attention networks, message passing, physics-informed learning
Dispatch layer	Converts estimated and predicted grid conditions into robust DER coordination recommendations	State estimates, GNN outputs, uncertainty sets, DER constraints, operator preferences	DER setpoints, flexibility requests, curtailment recommendations, operating envelopes, operator alerts	Chance constraints, distributionally robust optimization, sensitivity-based control, human-in-the- loop interfaces

Physical Grid Layer

Asset and topology modeling

The physical grid layer represents the distribution network as an asset-linked graph whose nodes correspond to buses, transformers, loads, and DER connection points, while edges correspond to lines, switches, and regulators. Topology-aware probabilistic state estimation research shows that topology changes can materially affect estimated system states and must be reflected in the operational model [16]. This layer therefore maintains not only static feeder data but also dynamic switching status, device connectivity, and phase information. Its output is a synchronized graph representation that downstream layers can interpret consistently.

Sensor and meter data acquisition

Sensor and meter data acquisition in this architecture is designed to handle heterogeneous data streams with different latencies and reliability levels. Multi-source state estimation research emphasizes that PMU, SCADA, AMI, and other measurement classes contribute different forms of visibility into power system operation [7]. The physical grid layer would time-stamp, validate, and align these streams before forwarding them to the state estimation layer. It would also preserve metadata about measurement quality so that uncertainty can be carried through the architecture.

Real-time grid mirror

The real-time grid mirror is the operational representation that links physical devices, measurements, topology, and controllable DERs into a continuously updated digital object. Digital twin principles for power systems stress that such a mirror must support bidirectional interaction, where field data update the model and model-based decisions can be communicated back to physical devices [2]. In the proposed architecture, the mirror does not directly dispatch DERs but prepares the structured, synchronized information required for estimation and analytics. This separation helps ensure that the physical grid layer remains a trusted source of operational context for all subsequent layers.

State Estimation Layer

Measurement fusion

The state estimation layer fuses heterogeneous measurements into a coherent operational state that can be consumed by GNN analytics and dispatch. Physics-aware neural network approaches for distribution system state estimation show that learned estimators can be structured around electrical constraints rather than relying on measurement data alone [17]. In the proposed architecture, classical estimation, Bayesian fusion, and learning-enhanced estimation could coexist as interchangeable estimation services. This layer would expose estimated voltages, injections, branch flows, and uncertainty descriptors through a standardized interface.

Handling bad data and loss

Handling bad data and communication loss is essential because real-time DER coordination cannot assume complete or perfectly reliable measurements. Deep unrolled approaches to real-time state estimation and forecasting suggest that estimation pipelines can be designed to operate dynamically as measurements arrive and system conditions evolve [18]. The proposed layer would therefore include bad-data detection, measurement-quality tagging, and fallback pseudo-measurement generation before publishing the operational state. These mechanisms would be expected to reduce the risk that corrupted or missing telemetry propagates directly into DER dispatch decisions.

Providing consistent state

The state estimation layer provides a consistent system state that aligns measurements, topology, and physical constraints into a usable digital-twin representation. Unrolled spatiotemporal graph convolutional networks for distribution state estimation and forecasting demonstrate the value of combining temporal dynamics with grid-structured representations [19]. In this architecture, the estimated state forms the bridge between the physical grid mirror and the GNN analytics layer. The consistency of this state is important because dispatch recommendations would otherwise be based on fragmented measurements rather than on an integrated view of the active distribution network.

GNN Analytics Layer

Graph modeling of grid topology

The GNN analytics layer models the distribution grid as a graph whose nodes, edges, and attributes represent buses, branches, phases, DERs, loads, switch states, and estimated electrical quantities. Spatio-temporal graph convolutional learning for grid applications shows that topology and temporal behavior can be jointly represented for physics-aware grid analytics [20]. In the proposed architecture, graph construction is not a preprocessing afterthought but a core interface between state estimation and learning. This allows the GNN layer to maintain electrical neighborhood relationships that conventional tabular machine-learning models may lose.

GNN for voltage and congestion prediction

Voltage and congestion prediction are central functions of the GNN layer because DER coordination must anticipate operating-limit violations before they become binding. Probabilistic physics-informed graph convolutional networks for voltage prediction show how uncertainty and grid physics can be incorporated into topology-aware prediction tasks [21]. In the architecture, the GNN layer would produce risk indicators for voltage deviation, line congestion, and localized constraint activation. These indicators would then be passed to the dispatch layer as decision-support signals rather than as final control actions.

GNN for DER flexibility characterization

The GNN layer can also characterize DER flexibility by learning how local injections, storage states, inverter limits, and network constraints interact across the feeder graph. Decentralized graph neural networks for power-flow balancing indicate that graph-based models can support distributed reasoning across electrically connected resources [22]. In the proposed architecture, DER flexibility would be represented as a topology-dependent capability rather than as an isolated resource quantity. This means that a DER’s usefulness for voltage regulation or congestion relief would depend on its location, operating state, and surrounding network conditions.

Learning and adaptation

Learning and adaptation are necessary because feeder topology, DER penetration, demand patterns, and communication availability change over time. Complex-valued spatiotemporal graph convolutional networks demonstrate that grid analytics can be designed to preserve electrical signal structure while learning from evolving power-system data [23]. Meta-learning enhanced graph attention methods further suggest that GNN models could adapt to new operating regimes or limited labeled data in distribution state estimation contexts [24]. **Table 2** summarizes the GNN model types that could be used in the architecture and the grid functions they would support.

Table 2. GNN Applications and Models in the Architecture

GNN model type	Grid function in the architecture	Graph representation	Primary architectural output	Interface with other layers
Graph convolutional network	Voltage-risk prediction and feeder-state pattern learning	Nodes as buses and DER points, edges as electrical connections, features as estimated voltages and injections	Voltage deviation indicators and localized sensitivity patterns	Receives estimated state from the state estimation layer and sends risk indicators to dispatch
Graph attention network	Identification of influential buses, constrained branches, and DERs with high operational leverage	Attention weights over neighboring nodes and edges using topology and operating-state attributes	Interpretable influence scores and priority zones	Supports operator awareness and dispatch prioritization
Message-passing neural network	Propagation of power-flow-related dependencies across radial or weakly meshed feeder topology	Iterative node-edge message exchange using electrical and operational features	Feeder-wide congestion and flexibility descriptors	Converts the grid mirror into dispatch-relevant network embeddings
Spatiotemporal GNN	Short-horizon prediction of evolving voltage, congestion, and flexibility conditions	Time-indexed graph snapshots with historical estimated states and DER behavior	Near-term operating trajectories and risk evolution	Supplies predictive inputs to uncertainty-aware dispatch
Physics-informed GNN	Learning constrained by power-system relationships and grid feasibility logic	Graph features augmented with electrical constraints, residuals, or physics-based penalties	Physically consistent analytics and constraint-aware predictions	Reduces mismatch between learned analytics and operational decision rules

Dispatch Layer

Uncertainty-aware decision framework

The dispatch layer converts estimated states, GNN outputs, DER constraints, and uncertainty descriptors into operational recommendations for DER coordination. Risk-aware distributionally robust optimal power flow research shows that uncertainty-aware formulations can support flexible resource use while respecting unbalanced distribution-network constraints [25]. In the proposed architecture, uncertainty is represented through confidence intervals, scenarios, ambiguity sets, or chance constraints depending on the available data and operational policy. The dispatch layer is therefore designed to make decisions that remain feasible under plausible deviations in load, renewable generation, topology, and measurements.

DER coordination optimization

DER coordination optimization in the architecture could generate active-power curtailment, reactive-power support, storage charging or discharging, flexible-load activation, and operating envelopes. ADMM-based distributed AC optimal power flow for multiperiod DER coordination illustrates how DER decisions can be coordinated across time while considering inverter Volt-Var behavior [26]. The proposed dispatch layer would not prescribe a single optimization algorithm but would define the inputs, outputs, and robustness requirements that such algorithms must satisfy. This allows centralized, distributed, or hybrid coordination schemes to be implemented within the same digital-twin framework.

Integration with GNN outputs

The dispatch layer integrates GNN outputs by translating topology-aware predictions into constraints, penalties, priorities, or advisory signals for optimization. Physics-informed GNN methods for collaborative reconfiguration and voltage regulation show that learned graph representations can support coordinated operational decisions in unbalanced distribution systems [27]. In the proposed architecture, voltage-risk indicators could tighten local constraints, congestion-risk indicators could prioritize flexibility activation, and graph embeddings could inform sensitivity approximations. This integration would allow dispatch to use learned insights while retaining explicit operational rules and operator oversight.

Human-in-the-loop override

Human-in-the-loop override is included because DER dispatch affects reliability, customer participation, equipment limits, and operational accountability. Fairness-aware distributed energy coordination research highlights that voltage-regulation decisions can involve allocation concerns across customers and resources, not only technical feasibility [28]. The architecture therefore includes operator dashboards, explainability summaries, override controls, and audit trails as part of the dispatch layer. **Table 3** summarizes how uncertainty sources, dispatch decisions, and robustness mechanisms are organized within the proposed design.

Table 3. Uncertainty Sources, Dispatch Decisions, and Robustness Mechanisms

Uncertainty source	Dispatch decision affected	Robustness mechanism	Architectural treatment
Renewable generation variability	Curtailment, storage scheduling, inverter reactive-power support	Scenario-based dispatch, chance constraints, forecast-error envelopes	Forecast uncertainty is attached to DER availability and propagated into dispatch feasibility checks
Load forecasting error	Flexible-load activation, voltage regulation, feeder congestion management	Distributionally robust constraints and adaptive operating margins	Load uncertainty is represented at node or zone level using confidence descriptors from the state estimation and analytics layers

Measurement noise and missing data	DER setpoint approval, constraint tightening, alarm prioritization	State-estimation confidence weighting and bad-data-aware dispatch filtering	Low-confidence states trigger conservative setpoints, operator alerts, or delayed automation
Topology uncertainty	Switching recommendations, congestion relief, voltage support	Topology scenario evaluation and secure fallback operating modes	Alternative graph states are evaluated before dispatch recommendations are released
DER availability uncertainty	Flexibility requests, storage dispatch, demand response activation	Reserve margins, priority ranking, and fallback resource selection	DER flexibility is modeled as conditional on communication, customer participation, and device status
Model mismatch	Optimization feasibility, GNN-informed sensitivity use, constraint enforcement	Human review, physics-based feasibility checks, and closed-loop correction	Dispatch recommendations are screened against physical constraints and updated as new measurements arrive

Validation Strategy

Simulation and co-simulation setup

The architecture could be validated through simulation and co-simulation environments that connect feeder models, DER controllers, communication emulation, state estimation services, GNN analytics, and dispatch logic. Uncertainty-aware coordinated dispatch studies for integrated energy systems show that validation environments can represent coupled uncertainty sources without requiring field deployment at the earliest stage [29]. In this article, validation is proposed as a future methodology rather than as a reported experiment. The simulation pathway would examine whether the layers exchange information correctly, preserve topology consistency, and support robust DER coordination workflows.

Hardware-in-the-loop and field pilot roadmap

A hardware-in-the-loop roadmap could connect real inverters, controller hardware, communication gateways, and real-time digital simulators to evaluate latency, interoperability, and operator interaction. Data-driven distributionally robust dispatch work for integrated power and heating systems illustrates how uncertain renewable conditions can be incorporated into operational decision frameworks that may later be tested in more realistic settings [30]. A field pilot could then begin with advisory dispatch, progress to supervised control, and eventually support bounded automation once trust and governance requirements are satisfied. The validation strategy is therefore designed to test architecture readiness rather than to claim performance outcomes.

Conclusion

This article proposed a layered digital-twin architecture for real-time DER coordination using state estimation, graph neural network analytics, and uncertainty-aware dispatch. The architecture separates physical grid mirroring, measurement fusion, topology-aware learning, and robust decision support into distinct but interoperable layers. This separation is intended to make the design understandable, maintainable, and adaptable to different utility environments. It also clarifies how DER coordination could evolve from monitoring toward structured operational intelligence.

The physical grid layer provides the synchronized representation of assets, topology, telemetry, and controllable DERs. The state estimation layer transforms heterogeneous and imperfect measurements into a coherent operational state. The

GNN analytics layer uses graph-structured representations to provide predictive and diagnostic insights about voltage, congestion, flexibility, and topology-dependent behavior. The dispatch layer converts these insights into robust coordination recommendations while preserving operator authority.

The architecture is conceptual and does not report experiments, measured performance, or quantitative validation results. Its value lies in defining responsibilities, data flows, interfaces, and uncertainty pathways for a next-generation distribution management environment. By treating uncertainty as a cross-layer design concern, the architecture supports more resilient DER coordination than designs that isolate uncertainty only inside the final optimization step. By treating topology as a core representation, it also aligns learning and dispatch with the physical structure of the distribution network.

Future work could implement the architecture in staged validation environments, beginning with simulation and co-simulation before moving toward hardware-in-the-loop and supervised field pilots. Such work would need to evaluate interoperability, cybersecurity, model governance, operator acceptance, and scalability across feeders with different DER penetration levels. The proposed architecture offers a blueprint for organizing those efforts without prescribing a single vendor platform or algorithmic implementation. It therefore provides a practical conceptual foundation for digital-twin-enabled DER coordination in active distribution networks.

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