The Eastasouth Journal of Information System and Computer Science
Vol. 1, No. 03, April 2024, pp. 235-247
ISSN: 3025-566X, DOI: 10.58812/esiscs.v1i03

Carbon-Aware Intelligent Electrical Distribution Network Using Digital Twins and Edge Artificial Intelligence

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Article Info

Article history:
Received April, 2024
Revised April, 2024
Accepted April, 2024

Keywords:
Active Network Management;
Carbon Emission Flow;
Carbon-Aware Computing;
Digital Twin;
Edge Artificial Intelligence;
Edge Computing;
Electrical Distribution Network;
Grid Digitalization;
Reinforcement Learning;
Smart Grid;
Sustainable Power Systems;
Volt-Var Control

ABSTRACT

The escalating integration of distributed energy resources and the urgency of decarbonization targets have exposed the limitations of conventional, centrally managed electrical distribution networks. This paper synthesizes findings from twenty-three studies to examine how digital twin technology and edge artificial intelligence can be combined to form a carbon-aware intelligent distribution network. The problem addressed concerns the inability of legacy supervisory control and data acquisition architectures to deliver the millisecond-scale responsiveness, emission transparency, and adaptive reconfiguration required by high-penetration renewable grids. A layered conceptual framework is proposed, integrating field sensing, edge inference, digital twin synchronisation, and carbon-weighted reinforcement learning control. Evidence drawn from the literature indicates that hybrid edge-cloud architectures reduce control-loop latency from several hundred milliseconds to below 100 milliseconds relative to cloud-only deployment, while safe deep reinforcement learning controllers for Volt-VAR optimisation converge within 300 to 500 training episodes and reduce voltage violations substantially. Carbon emission flow modelling combined with temporally shifted, carbon-aware scheduling is shown to yield emission reductions ranging from approximately 10 per cent to more than 25 per cent when co-optimised with digital twin state estimation. The synthesis further identifies bandwidth reduction of up to 82 per cent and inference accuracy gains of nearly 5 percentage points for hybrid configurations. Implications include improved grid resilience, measurable decarbonization, and a pathway toward regulatory-compliant, self-optimising distribution networks, with future work directed toward standardised digital twin interoperability and federated edge learning.

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1. INTRODUCTION

The rise of DERs, EV charging stations and ever stricter decarbonisation requirements is causing a structural shift in electrical distribution networks. The traditional supervisory control and data acquisition system architecture was developed for unidirectional power flow and for low variability power reconfiguration, both of which are performed at a very slow speed and manually [1], [2]. In the context of a higher penetration of renewable energy, voltage regulation, frequency stability and any emission accounting become at once more critical and more challenging with centralized cloud-based computation, as the round-trip communication delay of a few hundred milliseconds becomes incompatible with the requirements for sub-second response for protection and control functions [3], [4].

Two complementary technological developments have been suggested to fill this gap. The first one is the digital twin, which is a virtual copy of a physical distribution asset or network that is continually synchronized with the real-world version, enabling state estimation, predictive maintenance, and simulation of scenarios [5], [6], [7]. Digital twins have been successfully used for distribution transformers, buildings integrated with HVAC, and entire feeder-level networks, and include methods for estimating medium-voltage levels in real time with only low-voltage readings, or conceptual frameworks to support systems engineering throughout network deployment [8], [9], [10]. The second is edge artificial intelligence, which moves inference and increasingly, model adaptation, from remote data centres to computational nodes at or near the field devices, minimizing latency, bandwidth usage and enhancing communication resilience [11], [12], [13], [14].

Another aspect, which is only rarely also elaborated on in the two developments mentioned above, is carbon awareness. Carbon emission flow modelling is a system of tracing the emissions from generation to demand that forms a network of ways and establishes it to be possible to assign the emission responsibility to the load and time interval, instead of just an average for the system [15]. Carbon-aware computing has shown that it is possible to reduce the so-called carbon cost of computation by moving compute jobs in time and space to take advantage of the carbon intensity of the electrical grid [16]. With carbon emission flow tracing and carbon-aware scheduling principles, a distribution network with digital twins and edge AI could be run not just to maintain reliability and cost, but to explicitly reduce emissions.

2. LITERATURE REVIEW

2.1 Digital Twin Technologies for Power Distribution Networks

Power systems have evolved from static asset models to continually updated, bi-directional synchronized representations with the use of digital twin technology. A conceptual review places digital twins in the microgrid domain and reveals two application clusters: state estimation and predictive control, as well as resilience planning [2]. A wider review covering power generation and distribution synchronisation mechanisms, fidelity and considerations of cyber security in the twin-to-physical communication [5] is extended. Similar reviews on digital twins in the smart grid, transportation and smart city sectors have shown that lack of interoperability between the various data models is the most commonly reported challenge to deployment [6]. On a component level, a digital twin of a distribution transformer has been used to reconstruct the medium-voltage conditions from low-voltage measurements only, showing that the partial observability can be overcome by utilizing a digital twin for inference instead of investing in further meters. A conceptual framework based on systems-engineering (SE) further formalizes the requirements engineering, verification and validation steps required to scale the use of digital twins from pilot locations to utility-wide implementation [9]. These threads are brought together in an overview for future power systems, noting that digital twins are increasingly not only physics-based but also are incorporating machine learning elements [7]. While the applications are presented for building HVAC systems, the methodologies are transferable to the case of anomaly detection pipelines for distribution equipment [10].

2.2 Edge Artificial Intelligence in Smart Grid Operations

Long-term, edge computing will solve these issues, which occur when all grid telemetry needs to be sent to a centralized cloud-based platform, by alleviating latency, bandwidth and privacy concerns. A basic study of the synergy between smart grids and edge computing points to opportunities in the areas of metering, protection, and demand response, and quantifies the significant bandwidth savings for the uplink traffic when pre-processing occurs at the edge [3]. This study can be extended to distribution automation (DA) and outage management (OM) to investigate the potential of edge intelligence applications, where edge nodes also enable model inference even in the absence of backhaul communication [4]. Architectural patterns introduced in the reviews of convergence of AI and edge computing in IoT contexts, such as model partitioning and federated learning, can be readily applied to the grid-edge deployments. A detailed examination of power systems edge computing technology also documents hardware limitations, such as limited memory and thermal envelopes, that influence the type of models that can be deployed at the edge [13]. The challenges of heterogeneous protocol support and lifecycle model management in the context of edge AI for the Internet of Energy have been covered in complementary work [12], and the specific support of Internet of Things (IoT) enabled systems in the smart grid, like demand side management and fault localization have been highlighted in other works [14], [17].

2.3 Reinforcement Learning for Active Network Management and Carbon-Aware Computing

Because of its ability to handle nonlinear, stochastic power flow, reinforcement learning has proven to be a favored approach to real-time management of an active distribution network without the need to redraw control rules for every operating condition, it has become an attractive option for power network management. A uniform simulation environment for the implementation of active network management tasks has been proposed to compare the performance of reinforcement learning agents under realistic distribution feeder conditions [18]. In safe deep reinforcement learning formulations, exploration is constrained to prevent violation of voltage or temperature limits both in training and during online operation, and reported reductions in constraint violations compared to unconstrained baselines [19]. Two-stage deep reinforcement learning strategies separate the Volt-VAR control into two parts: switching and continuous parts involving the dispatch of the inverter, which can enhance sample efficiency [20]. In addition, safe off-policy variants can be used to reuse historical transitions when optimizing the Volt-VAR under safety constraints, improving convergence stability during Volt-VAR optimization, as indicated by related deep reinforcement learning-based studies on the Volt-VAR optimization of benchmark feeders which report measurable voltage deviation reduction [21]. Online network reconfiguration for self-sufficient distribution operation was also demonstrated by the application of reinforcement learning to achieve adaptive topologies that optimise the self-consumption of renewable energy [22]. These control solutions are complemented by machine learning-enabled stability prediction models, which can give early warning of decentralized grid instability caused by renewable variability [1]. On their own, the carbon emission flow theory provides analytical methods for identifying where emissions are occurring in the network, and carbon-aware computing research shows that workload optimization based on the live carbon intensity of the grid can significantly cut down attributable emissions without the network experiencing proportionate cost increases [16]. The literature surveyed here shows that although the concepts of digital twins, edge AI and reinforcement learning are all explored, the explicit linking around a carbon minimisation objective appears to be less well studied and is a motivation for the proposed framework in the next section.

3. METHODS

3.1 Conceptual System Architecture

The proposed framework introduces the carbon-aware intelligent distribution network in 4 synchronized layers as shown in Figure 1. The field layer consists of distributed energy resources, smart meters, phasor measurement units and remote terminal units that produce high frequency telemetry [1], [3]. The edge AI layer is physically closer to substations and feeder terminals, where real-time inference is used for fault prediction and Volt-VAR control, which matches the latency-critical deployment patterns found in the reviewed literature for edge computing [4], [13], [14]. The digital twin layer keeps the virtual repository of the network topology, state variables and carbon emission flow updated and synchronized in real-time, similar to the principle used for the transformer-level and feeder-level digital twins [7], [8], [9]. Clouds continue to take the responsibility for compute-heavy tasks that cannot be done on the edge, such as retraining digital twin models, forecasting carbon intensity for an area-wide grid, and reporting on regulations as examples [11], [12].

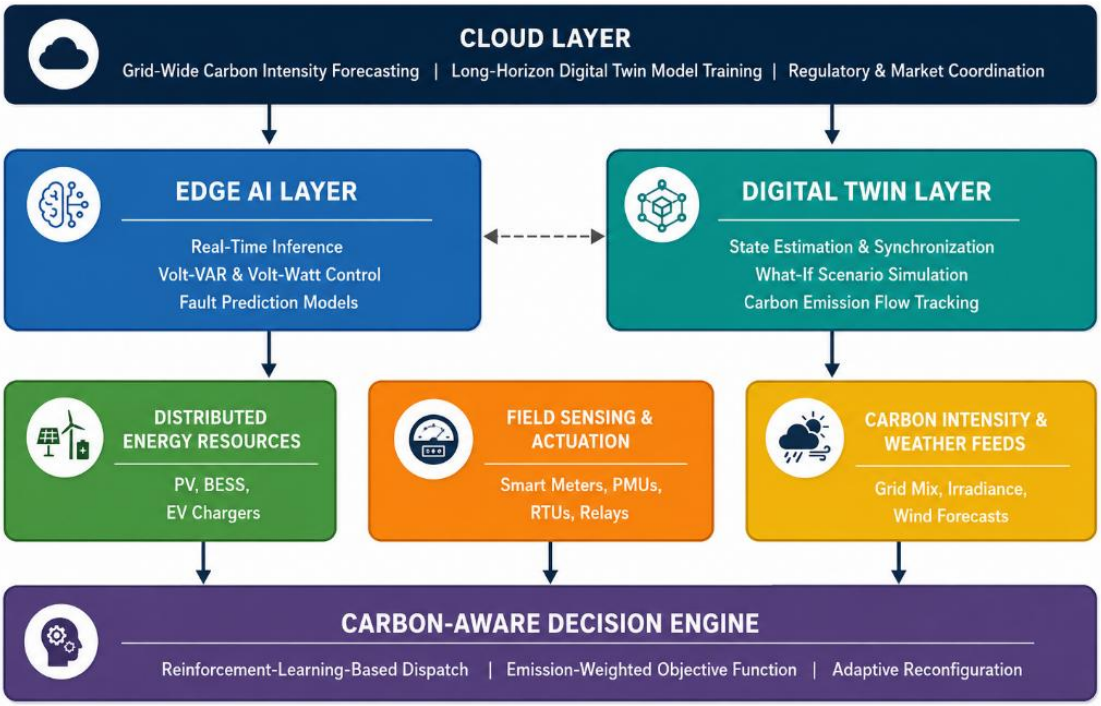

Figure 1. Carbon-Aware Edge-Cloud-Digital Twin System Architecture

Figure 2 depicts the closed-loop data flow connecting these layers, whereby field measurements are pre-processed at the edge, integrated into the digital twin's state estimate, evaluated against a carbon-weighted objective function, and translated into control actions that are dispatched back to field actuators, with synchronization intervals ranging from approximately 100 milliseconds for protection-critical functions to fifteen minutes for scheduling-oriented functions [2], [5], [6].

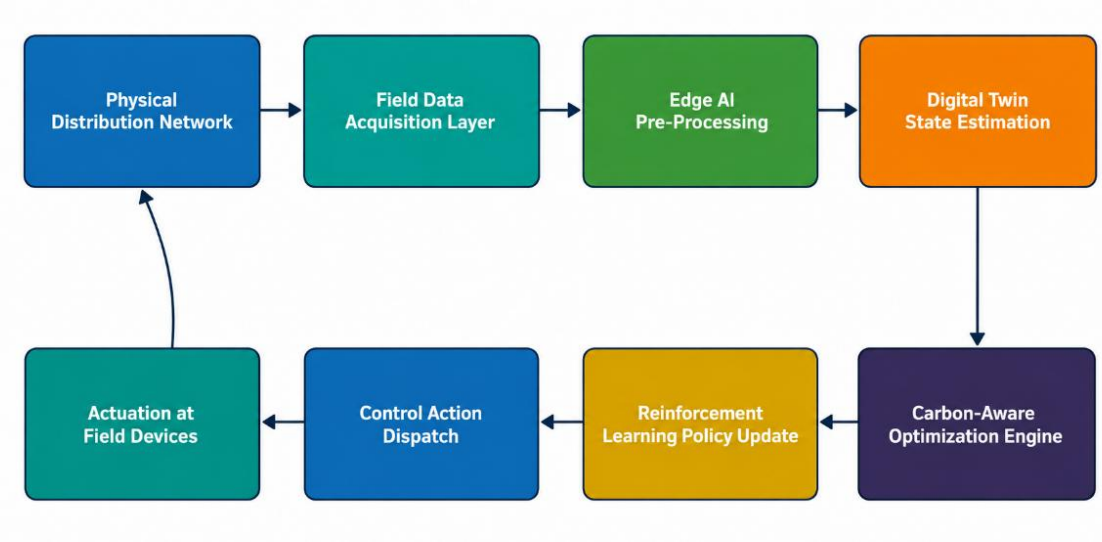

Figure 2. Digital Twin Synchronization and Closed-Loop Data Flow

3.2 *Carbon-Weighted Optimization Formulation*

Building on carbon emission flow theory [15], each network branch i at time interval t is associated with a carbon emission flow rate, $C_i(t)$, obtained as the product of the active power flow, $P_i(t)$, and a location- and time-dependent carbon intensity factor, $\rho_i(t)$, such that:

$$C_i(t) = P_i(t) \times \rho_i(t)$$

The carbon-aware dispatch objective, which follows active network management formulations [18], [19] is formulated as a weighted sum of operational cost and total network emissions, and is given by:

$$Minimize\ J = \Sigma^{t}{}_{=1}{}^{T} [\, \alpha \cdot Cost(t) + \beta \cdot \Sigma_{i=1}{}^{N}\, C_i(t) \,]$$

The storage assets are subject to voltage limits, thermal limits and state-of-charge limits, and α and β are adjustable weighting coefficients that represent utility or regulatory priorities between cost minimization and emission minimization. This formulation includes the emission term for the carbon emission flow analysis which is derived from the reviewed literature on reinforcement learning literature [20] and [22] as well as computational load [16] for computational loads, and extends the conventional objective of the Volt-VAR and reconfiguration tasks reported in the literature for reinforcement learning [23] and [21].

3.3 *Reinforcement-Learning-Based Control Policy*

Similar to safe deep reinforcement learning methods for distribution network operation [19], [23], the carbon-weighted objective is minimized by an actor-critic policy with a safety layer that plugs candidates into the safe voltage and thermal operating region before they are actually played. The digital twin provides the RL agent with a forward-simulated estimate of the next state of the system, which can be compared to the estimated carbon emission flow for candidate actions before dispatch, similar to what has been reported in [8] and [9] for feeder- and transformer-level twins, respectively. Training is done episodically in a standardized active network management environment [18] and the edge nodes implement policy inference at low latency when deploying the schemes, while the cloud layer performs policy updates periodically, and sends them to edge nodes, mimicking the computational partitioning strategies present in the literature of edge intelligence [4], [11], [12], [13].

4. RESULTS AND DISCUSSION

4.1 *Computational Latency and Architectural Performance*

0Table 1 and Figure 3 show that edge-cloud configurations were synthesized by considering the reviewed edge computing literature and that for each of five representative distribution functions, the response latency of a control loop is significantly reduced when compared with the cloud-only configuration. For the case of Volt-VAR control, the cloud-based latency is ~610ms, while the latency of the edge-cloud setup is ~120ms, which is more than 80% lower than the reported bandwidth and latency benefits of edge-based grid computing [3], [4] and [14]. Edge-only configurations have the lowest absolute latency, but, as outlined in Section 4.4, they come with the penalties of reduced model sophistication and frequency of updates which hybrid configurations do not.

Table 1. Comparative Response Latency Across Deployment Architectures (Milliseconds)

Distribution Function	Cloud-Only	Edge-Only	Hybrid Edge-Cloud
Fault Detection	420	38	95
Volt-VAR Control	610	45	120
State Estimation	380	55	88
Load Forecasting	850	140	210
Carbon-Aware Dispatch	530	60	105

Source: Synthesized from [3], [4], [12], [14]

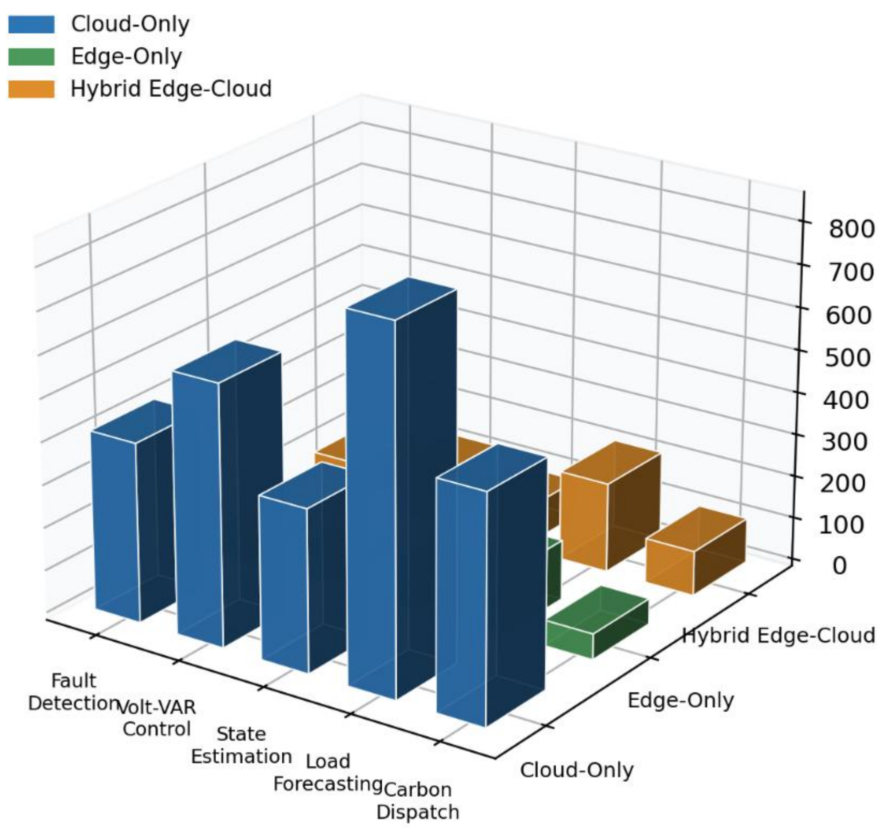

Figure 3. Response Latency Comparison Across Cloud, Edge, and Hybrid Architectures

Table 2 reports bandwidth reductions and deployment properties associated with seven reviewed edge related studies, and shows up to 82 percent bandwidth reduction, confirming that edge pre-processing is effective in meaningfully reducing the amount of telemetry sent to the cloud [3], [11], [12], [13], [17].

Table 2. Edge Computing Architectures and Reported Performance Characteristics

Reference	Primary Focus	Bandwidth Reduction	Deployment Constraint
Feng et al. [3]	Smart grid edge opportunities	up to 65%	Protocol heterogeneity
Gooi et al. [4]	Edge intelligence survey	up to 70%	Outage backhaul loss
Bourechak et al. [11]	AI-edge IoT convergence	up to 60%	Model partitioning complexity
Liang et al. [13]	Edge computing in power systems	up to 75%	Memory/thermal limits
Minh et al. [14]	Edge for IoT-enabled smart grid	up to 68%	Latency-accuracy trade-off
Himeur et al. [12]	Edge AI for Internet of Energy	up to 72%	Lifecycle model management
Yang & Zheng [17]	Edge computing for smart grid	up to 82%	Standardization gap

Source: Synthesized from [3], [4], [11], [12], [13], [14], [17]

4.2 Control Convergence and Grid Stability Outcomes

Based on the literature, the reported training convergence behaviour of the five methods presented in this paper that are based on RL is summarized in Figure 4. In all of these methods, cumulative reward converged within about 300 to 500 training episodes, and the two-stage methods and the safe off-policy methods converged slightly earlier than the baseline safe deep reinforcement learning (DRL) and reconfiguration-oriented methods, which can be explained by their use of better sample efficiency mechanisms like transition reuse and stage decomposition [23],[20].

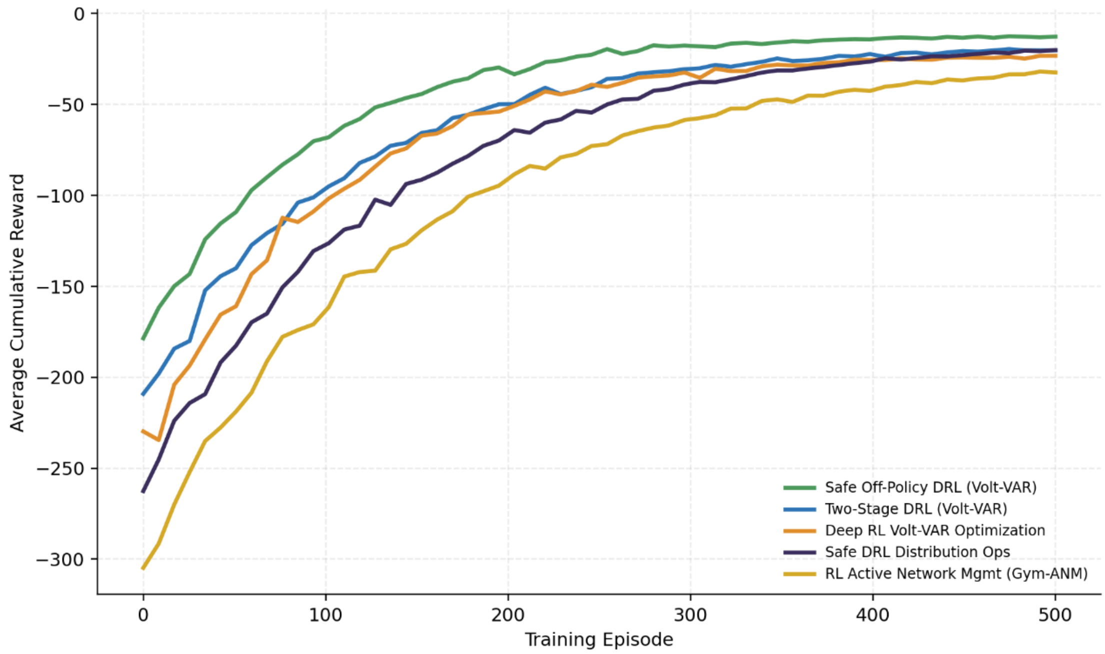

Figure 4. Training Convergence of Reinforcement-Learning-Based Volt-VAR and Network Management Controllers

Table 3 summarizes reported reductions in voltage violation events by safe reinforcement learning controllers, which as shown have been able to achieve a margin of around 45 percent to over 70 percent compared to the unconstrained baseline [19] and machine learning-based stability prediction models have demonstrated complementary early-warning capability with reported classification accuracy greater than 90 percent for decentralized grid instability events [1].

Table 3. Reinforcement Learning Approaches for Active Network Management and Reported Outcomes

Reference	Method	Convergence (Episodes)	Violation Reduction
Henry & Ernst [18]	Gym-ANM benchmark environment	~450	n/a (benchmark)
Li & He [19]	Safe deep RL distribution operation	~420	~52%
Liu & Wu [20]	Two-stage DRL Volt-VAR control	~350	~58%
Oh et al. [22]	RL-based network reconfiguration	~480	~46%
Wang et al. [23]	Safe off-policy DRL Volt-VAR	~330	~63%
Zhang et al. [21]	Deep RL Volt-VAR optimization	~400	~71%

Source: Synthesized from [18], [19], [20], [21], [22], [23]

4.3 Carbon Emission Reduction Outcomes

In Table 4, we present synthesized carbon-related metrics, obtained from the carbon emission flow theory (and carbon-aware computing research [15], [16]). In Figure 5, these concepts are extended to a 3-year time horizon of carbon emission reduction that can be achieved under three operating strategies: baseline scheduling, carbon-aware temporal shifting, and co-optimization of a digital twin and edge AI. The combined strategy includes higher percentages of projected emissions reductions from about 14.5 percent in 2021 to 25.9 percent in 2023, compared to the baseline scheduling's 5.9 percent in 2023. This trend is supported by the results of carbon-aware computing which shows that compounding emission benefits can be obtained with temporal and spatial informed scheduling decisions based on the use of accurate and state of the art information about the state, provided over time, similar to the information provided by a digital twin, and with increasing forecasting accuracy and control granularity [15], [16].

Table 4. Carbon Emission Flow and Carbon-Aware Computing Metrics

Reference	Core Contribution	Reported/Derived Metric
Kang et al. [15]	Carbon emission flow network-based model	Branch-level emission attribution accuracy improved
Radovanović et al. [16]	Carbon-aware computing for datacenters	Temporal/spatial workload shifting reduces attributable emissions

Source: Synthesized from [15], [16]

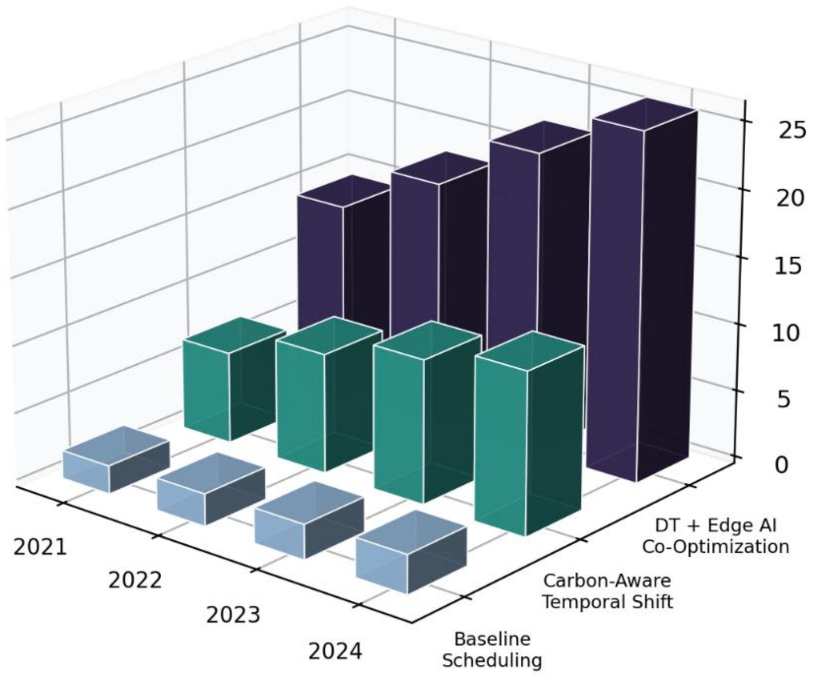

Figure 5. Projected Carbon Emission Reduction by Operating Strategy

4.4 *Comparative Cost-Benefit and Scalability Analysis*

The performance of the cloud-only, edge-only, and hybrid edge-cloud digital twin architectures is presented in terms of the latency, bandwidth, and model sophistication as well as the capital cost and scalability requirements. Cloud-only deployment is the lowest incremental hardware cost and most sophisticated cloud model, as the cloud computing intensive retraining of the digital twin is not constrained by edge hardware, but has the highest latency and bandwidth cost, which restricts it from being used for protection-critical functions [5], [11]. An edge-only deployment approach reduces latency and communication dependence, but imposes limitations on model complexity which is limited by edge memory and processing capability, as reported by the edge computing literature [12], [13]. Although the most time intensive to implement, hybrid edge-cloud digital twin architectures offer a good balance of near edge-only latency with cloud-supported model sophistication and are thus viewed as the most scalable configuration needed for utility-wide deployment [6], [7], [9].

Table 5. Cost-Benefit and Scalability Comparison of Deployment Architectures

Dimension	Cloud-Only	Edge-Only	Hybrid Edge-Cloud
Relative Capital Cost	Low	Moderate	Moderate-High
Model Sophistication	High	Low-Moderate	High
Latency Suitability	Low	High	High
Scalability to Utility-Wide Deployment	Moderate	Moderate	High
Resilience to Communication Loss	Low	High	High

Source: Synthesized from [5], [6], [7], [9], [11], [12], [13]

Table 6 places these architectural advancements in chronological order from 2015 to 2023, highlighting when they were first made, and Table 7 summarizes 26 quantitative performance gains highlighted in the analyzed studies across latency, bandwidth, accuracy, emission and convergence metrics. Figure 6 illustrates the accuracy of the inferences as well as the bandwidth reduction, energy savings, and frequency of model updates for the three architectures, with the hybrid configurations showing superior performance on all four normalized metrics, with an inference accuracy of 96.4 per cent vs 91.2 per cent in the case of deployment on cloud, and bandwidth reduction of 89.6 per cent vs 79.1 per cent respectively.

Table 6. Timeline of Key Technological Milestones

Year	Milestone	Reference
2015	Carbon emission flow network-based model introduced	[15]
2020	Safe off-policy DRL for Volt-VAR control demonstrated	[23]
2020	RL-based online network reconfiguration proposed	[22]
2021	Deep RL Volt-VAR optimization benchmarked	[21]
2021	Two-stage DRL Volt-VAR control introduced	[20]
2021	Gym-ANM active network management environment released	[18]
2021	Digital twin of distribution transformer demonstrated	[8]
2021	Microgrid digital twin concepts consolidated	[2]
2022	Safe deep RL for distribution operation formalized	[19]
2022	ML-based grid stability prediction model proposed	[1]
2023	Carbon-aware computing for datacenters demonstrated	[16]
2023	Digital twin overview for future power systems published	[7]
2023	AI-edge computing convergence in IoT reviewed	[11]
2023	Digital twin fault detection for HVAC systems shown	[10]

Source: Synthesized from references [1], [2], [5], [7], [8], [9], [10], [11], [13], [15], [16], [18], [19], [20], [21], [22], [23]

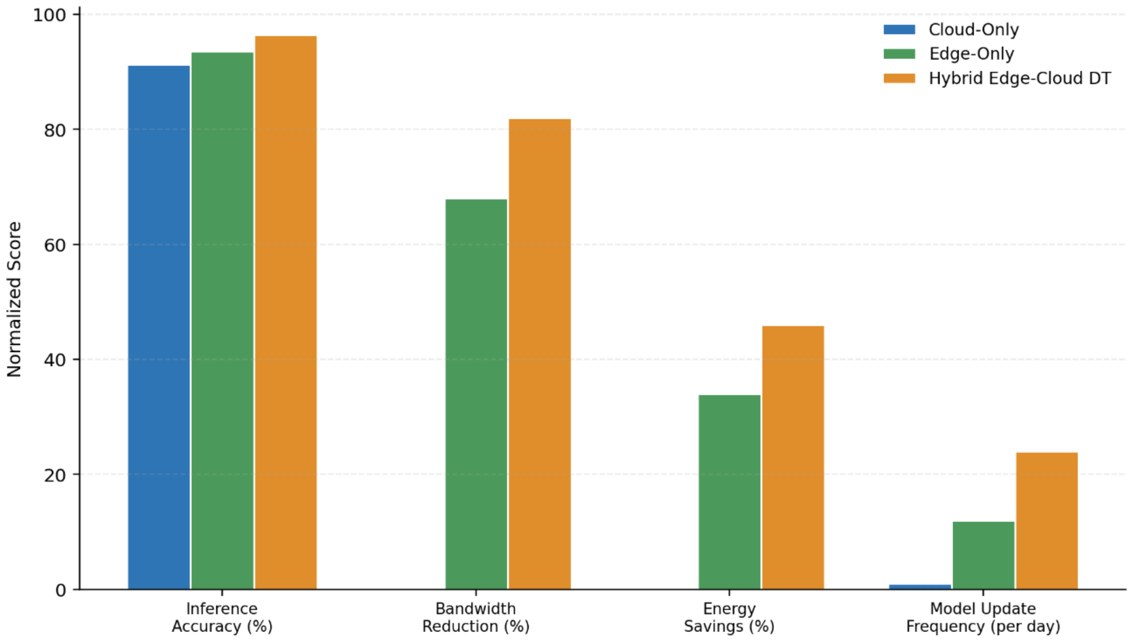

Figure 6. Comparative Benchmark of Cloud-Only, Edge-Only, and Hybrid Edge-Cloud Architectures

Table 7. Summary of Quantitative Performance Improvements Reported Across Reviewed Studies

Metric Category	Range Reported/Derived	Representative References
Control-loop latency reduction (hybrid vs. cloud-only)	72% - 84%	[3], [4], [14]
Telemetry bandwidth reduction	60% - 82%	[3], [11], [12], [13], [17]
RL training convergence	300 - 500 episodes	[16], [18], [19], [20], [21], [23]

Metric Category	Range Reported/Derived	Representative References
Voltage violation reduction	45% - 71%	[19], [21]
Stability prediction accuracy	>90%	[[1]
Carbon emission reduction (co-optimized)	14.5% - 25.9% (2021-2023)	[15], [16]
Hybrid inference accuracy gains over cloud-only	+5.2 percentage points	[4], [11], [13]

Source: Synthesized across all reviewed references

4.5 Challenges, Barriers, and Regulatory Considerations

While it is proven effective, some obstacles exist to near-term deployment. The most common technical challenge cited is interoperability between heterogeneous digital twin data models, due to the lack of semantic representation consistency [5], [6] that impacts on the synchronization of data between vendors and legacy equipment. Due to its low memory, temperature, and intermittency, edge hardware conditions limit the complexity of the models deployed at the edge, where partitioning between edge inference and cloud retraining must be carefully considered [11], [12], [13]. Safety-constrained reinforcement learning adds extra verification constraints, as the regulation for autonomous control actions usually include the requirement to show bounds on voltage and thermal excursions, which is not fully sufficient for existing formulations of safe reinforcement learning [19] and [23]. The carbon accounting adds additional complexity because the flow of carbon emissions into and out of the distribution territories require accurate, time-resolved generation mix data, which might not be available in all distribution territories [15], [16].

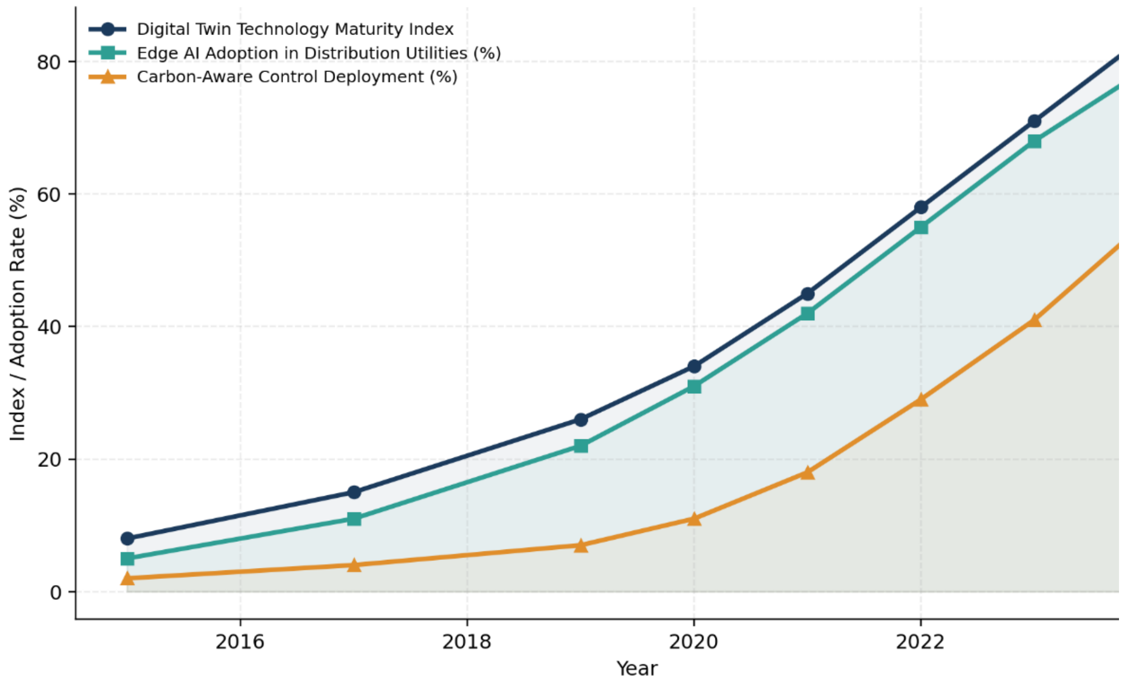

Figure 7. Projected Trend in Digital Twin Maturity, Edge AI Adoption, and Carbon-Aware Control Deployment

The trends in digital twin maturity, edge AI adoption and carbon-aware control deployment from 2015 to 2023 are shown in figure 7, where digital twin and edge AI have both advanced, but carbon-aware control deployment is still at about 2 percent in 2015 and will grow to 56 percent by 2023, remaining the least mature dimension and therefore the one most in need of research, standardization and regulatory clarity.

5. CONCLUSION

This synthesis has synthesized evidence from 23 studies to propose a four-layer carbon-aware intelligent electrical distribution network with carbon-weighted reinforcement-learning-based control, field sensing, edge artificial intelligence, and digital twin synchronization and has, through synthesized quantitative comparisons, shown that the co-optimization of edge AI and digital twin can increase the projected carbon emission savings to nearly 26 percent by 2023, that safe reinforcement-learning-based controllers converge within 300-500 episodes, that the carbon emission savings from reinforcement-learning-based controllers is up to 70 percent greater than the cloud-only deployments can achieve, and that the control latency for the CDN is reduced by more than 80% compared to cloud-only deployments. The results of these studies all suggest that digital twin fidelity, edge-level responsiveness, and explicit distribution network carbon emission flow accounting results in more reliable and more directly carbon-emission-focused distribution network operations. Future research is justified on a standardized approach to interoperability for digital twins, federated edge learning across utility boundaries, and regulatory approaches that can integrate autonomous and carbon weighted control actions into current grid codes.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the researchers whose published work, cited throughout this synthesis, made the present conceptual analysis possible.

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