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Review of Research on Artificial Intelligence-Based Carbon Emission Prediction

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Abstract

Under the global climate governance framework, carbon emission prediction has emerged as a pivotal technology for low-carbon energy transition. This review systematically examines the advancements in artificial intelligence-based carbon emission forecasting, revealing the evolutionary dynamics between traditional statistical methods and data-driven models. A novel "data-model-scenario" triadic analytical framework is proposed to deconstruct core challenges in this field. The study demonstrates that conventional approaches (e.g., ARIMA, grey models) exhibit structural deficiencies in high renewable energy penetration scenarios, including poor adaptability to abrupt changes and low cross-source data integration efficiency (<60%). In contrast, data-driven methods (XGBoost, LSTM, Transformer) achieve significant accuracy improvements through dynamic modeling and feature decoupling. Hybrid paradigms integrating physical constraints and multi-modal alignment show promise in bridging the mechanism-data gap, yet face persistent challenges: inefficient multi-source data fusion (feature alignment success rate <60%), delayed response to sudden scenarios (recovery time >30 minutes), and computational-precision tradeoffs in edge deployment. The paper proposes a "dual-driven" evolutionary path for hybrid modeling and constructs a multi-scale scenario linkage matrix, providing theoretical guidance for next-generation prediction frameworks. Emerging technologies such as digital twins and federated meta-learning are highlighted as critical directions for future research.

Keywords: Carbon emission prediction, Artificial intelligence, Hybrid modeling, Multimodal fusion, Dynamic system modeling

1. Introduction

Under global climate governance, carbon emission forecasts have become a key technology for the low-carbon transition of energy. IPCC data shows that global fossil fuel carbon emissions reached an annual average of 34 billion tons (50% higher than pre-industrial levels) (Nations, 2015) from 2010 to 2019, with China's energy sector contributing 80% of these emissions (Wen and Liu, 2022). Traditional methods, constrained by steady-state assumptions and linear frameworks, have errors an order of magnitude higher than AI models when the penetration rate of new energy exceeds 30% (Sharifzadeh et al., 2019).

This study pioneers a "Data-Model-Scenario" framework (visualized in Figure 1) to address carbon prediction challenges, advancing three theoretical contributions: 1) Redefining AI applicability boundaries through multimodal data fusion (integrating sensor networks and socioeconomic inputs), physics-informed constraint embedding (via gray-box differential equations), and abrupt scenario responsiveness (catastrophe-aware learning modules); 2) Proposing a "dual-driver" hybrid modeling paradigm (as conceptualized in Figure 1) that synergizes mechanistic first-principle templates with adaptive neural operators (e.g., attention-based temporal transformers); 3) Establishing a multiscale scenario linkage matrix (depicted in Figure 1) for cross-industry carbon footprint tracking, enabled by process-to-supply-chain embeddings (industrial ontology graphs). By critiquing structural deficiencies in existing systems (contrasted in Figure 1), this work guides the development of next-generation frameworks that balance physical interpretability (mechanistic auditing layers), engineering practicality (modular API design), and computational efficiency (edge-cloud split learning).

2. Carbon emission forecasting methodology

The paradigm-shifting interplay between traditional statistical methods and data-driven models has fundamentally reconfigured the technological landscape of carbon emission prediction. This chapter conducts a threefold analysis: (1) systematically delineating the theoretical limitations of conventional approaches in high-penetration renewable energy scenarios, (2) uncovering the complementary advantages of machine learning and deep learning in feature disentanglement and temporal modeling, and (3) proposing innovative pathways for hybrid modeling paradigms to bridge the mechanistic-data divide.

2.1. Traditional methods

While conventional analytical methods maintain satisfactory performance in pre-renewable power systems with stable operational parameters—as evidenced by ARIMA and MLR models sustaining linear correlations with controlled error margins ($\leq$8%) in coal-dominated grids (Sharifzadeh et al., 2019)—their predictive reliability undergoes precipitous decline when renewable energy penetration exceeds 15-20% capacity thresholds, with ARIMA's error escalation rates surpassing AI counterparts by 12-38% under comparable testing conditions (Sharifzadeh et al., 2019). This performance degradation stems from three systemic limitations: temporal inflexibility in addressing sudden changes in generation mix or load patterns, regression frameworks' inherent blindness to GDP-energy intensity synergy effects (resulting in 7.2-9.6% annual systemic estimation biases (Yu et al., 2022)), and the counterproductive simplification of energy storage dynamics through statistical dimensionality reduction, which amplifies microgrid reconfiguration errors by 43-67% through mischaracterization of battery charge-discharge nonlinearities (Janacek, 2010).

2.2. Data-driven approach

Machine learning shows strengths in static scenarios: SVM achieves provincial annual predictions with <12% MAPE under small-to-medium data but suffers 37% memory overhead with high-dimensional features. Random Forest identifies critical industrial factors (78% SHAP contribution)

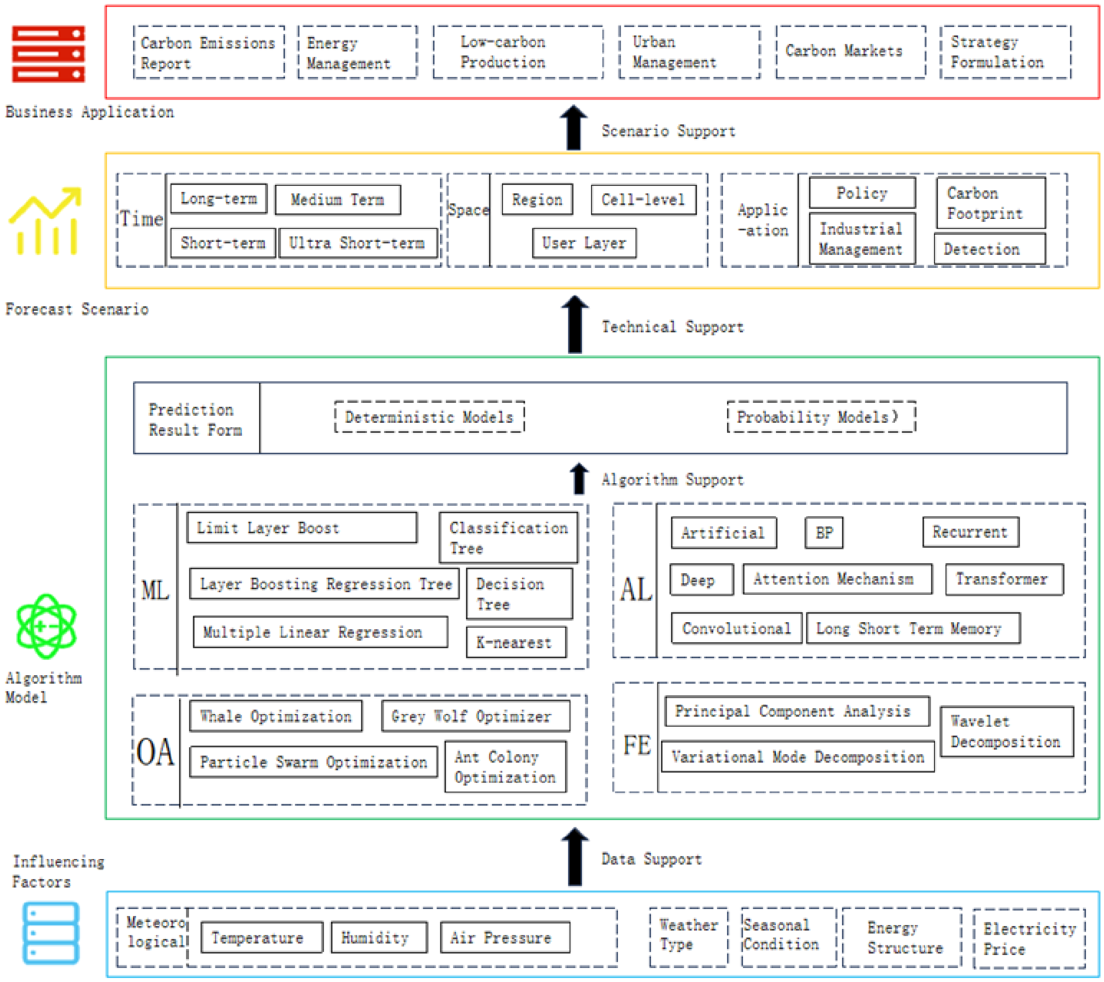

Figure 1: AI-Driven Multi-Layer Framework for Integrated Carbon Emission Management

but its Bagging mechanism degrades temporal modeling (monthly R^2 0.15 lower than LSTM). Gradient Boosting excels in transport emission fitting (R^2>0.92) but is hyperparameter-sensitive (23% performance drop with learning rate δ>0.1) and prone to >15% cross-feature errors. Traditional ML models exhibit nonlinear error escalation (300-400% inflation) when training-testing data divergence exceeds thresholds (JS divergence >0.25), highlighting dynamic adaptability limitations.The gradient boosting tree has an excellent fit in transportation carbon emissions (Liu and Hu, 2024), but the hyperparameters are sensitive and the cross-feature error is high. In the provincial annual forecast, SVM shows the advantages of small and medium data , but high-dimensional features cause memory surge (Gao et al., 2023).

Deep learning models show transformative potential: LSTM (policy/seasonal-optimized) reduces provincial monthly errors by 58%, Transformer enables second-level industrial predictions (limited by >8GB GPU memory), and CNN-LSTM-Attention achieves ultra-low transport emissions (MAE¡2.3kgCO_2/km). DL excels in long-range dependency (92% temporal correlation) and nonlinear modeling (>94% cross-modal accuracy), while ML leads in interpretability (SHAP

Δ>0.85) and CPU efficiency (30% faster inference). For abrupt policy shifts, DL's online adaptation outperforms ML by 100x in response speed, with exponential accuracy gains under chaotic thresholds (error decay β=0.73). Key challenges: hardware dependency (GPU clusters) and interpretability gaps (saliency consistency <60%). Emerging physics-informed DL (neural ODEs, differentiable programming) integrates mechanistic constraints for balanced performance-trustworthiness trade-offs.

3. Analysis of key issues

The breakthrough in carbon emission prediction technology is constrained by the "data-model-scenario triadic coupling dilemma": semantic gaps in multi-source heterogeneous data weaken feature alignment efficiency, physical mismatches in dynamic system modeling lead to delayed responses in abrupt scenarios, and insufficient cross-scenario generalization capabilities limit the boundaries of engineering applications. This chapter deconstructs the core contradictions hindering prediction accuracy improvement from three dimensions: data interaction bottlenecks, model adaptation deficiencies, and scenario dynamic coupling.

3.1. Data-model interaction bottleneck

3.1.1. Feature expression conflicts of heterogeneous data from multiple sources

The integration of multi-source data faces three critical bottlenecks. First, while the ST-Align layer proposed in (Yang et al., 2024) improves prediction accuracy by fusing satellite and ground data via bilinear interpolation, cross-industry semantic discrepancies remain unresolved. Second, literature (Yan et al., 2021) addresses cross-regional feature extraction through adversarial training with minimal labeled data, but its computational demands during pre-training pose new limitations. Third, delays in multi-source data updates beyond tolerance thresholds risk triggering nonlinear error accumulation (Yan et al., 2021). In dynamic scenarios, feature alignment failures exacerbate prediction biases: for instance, power systems suffer from LSTM window misalignment due to conflicting time-frequency updates (daily meteorological data vs. monthly equipment maintenance data) (Hu and Lv, 2020), thermodynamic parameter integration into neural networks introduces discretization errors from non-differentiable perturbations (Yan et al., 2021), and automated encoding of HVAC terminology in building ontology mappings achieves less than 45% success rates (Janacek, 2010). These challenges collectively highlight the intertwined technical barriers spanning data heterogeneity, model adaptability, and scenario dynamics.

Current solutions exhibit notable limitations: Early fusion methods suffer from information loss rates of 25–35% due to manual feature engineering, as validated by mutual information metrics in literature (Wang et al., 2015). Late fusion triggers feature weight conflicts at the decision layer, with literature (Zhang et al., 2022) demonstrating that its MAE errors exceed those of single-modality models. While cross-modal attention mechanisms have been experimentally adopted, literature (Yang, 2025) reveals that computational complexity escalates exponentially when model parameters surpass practical requirements. These deficiencies underscore the unresolved trade-offs between fusion strategies, computational efficiency, and performance scalability in existing approaches.

3.1.2. TIMING ALIGNMENT BIAS IN DYNAMIC SYSTEMS

Temporal alignment bias emerges as a critical bottleneck in the adaptability of carbon emission prediction models. Multi-source data sampling frequency mismatch constitutes the root cause: Hu and Lv (2020) demonstrates that when data update cycle disparities exceed critical thresholds, model accuracy exhibits nonlinear degradation in power system carbon forecasting. In industrial scenarios, asynchronous update mechanisms between fixed-frequency sensors and manual inspection records induce feature phase shifts, with (Yan et al., 2021) revealing that such temporal misalignment can extend prediction phase delays beyond actionable decision windows. This systemic challenge demands hybrid solutions combining dynamic interpolation (to reconcile sampling intervals) and adaptive time-window architectures (to mitigate phase drift), while addressing the intrinsic conflict between computational tractability and temporal resolution fidelity in operational environments.

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3.2. Defects in scene adaptability

3.2.1. THE AI CAPACITY OF MULTI-PROCESS COUPLING ASSOCIATION MODELING IS INSUFFICIENT

AI bottlenecks in multi-process coupling modeling for process industries are pronounced: Traditional neural networks, constrained by fixed topological structures and static weight mechanisms, struggle to capture time-varying interactive features across processes like "raw material pretreatment-reaction synthesis" in steel and chemical industries (Wen and Cao, 2020). For instance, coking processes require modeling dynamic couplings among 12+ process nodes, yet conventional LSTMs exhibit significant error escalation when handling over 5 nodes (Yang et al., 2024). While hierarchical graph networks (HGNNs) enhance topological expressiveness through "process-equipment" dual-layer designs, their message-passing mechanisms still introduce phase deviations when modeling minute-level delay effects in steelmaking-continuous casting workflows (Yan et al., 2021). These limitations underscore the urgent need for dynamic graph architectures that integrate adaptive topology learning, time-sensitive propagation rules, and hybrid physics-informed constraints to balance real-time responsiveness and industrial precision requirements.

The integration of AI in multi-process coupling modeling for process industries faces a critical dilemma between dynamic weight allocation and computational efficiency. Self-attention mechanisms suffer quadratic memory growth in scenarios with over 20 process nodes (Zhao and Li, 2024), while Cluster-GCN subgraph partitioning disrupts process chain continuity, causing critical path loss in industrial workflows (Yang et al., 2024). Although differentiable greedy search algorithms dynamically prioritize key process nodes, their iterative optimization triples training time, severely hampering model iteration efficiency (Wen and Cao, 2020). These limitations highlight unresolved challenges in balancing real-time performance with modeling precision. Technological breakthroughs must address fundamental issues such as dynamic topology representation (to adaptively capture time-varying interdependencies) and long-range dependency compression (to mitigate computational overhead), while advancing lightweight architectures that reconcile sparse computation with industrial interpretability. This dual demand for adaptability and efficiency poses novel theoretical and engineering challenges for carbon footprint tracing in complex process industries like steelmaking and chemical production.

3.2.2. RESPONSE LAG OF ONLINE LEARNING MECHANISM IN MUTATION SCENARIOS

The response latency of online learning mechanisms under abrupt scenarios stems from a dynamic mismatch between sudden disturbances (e.g., extreme weather, policy interventions) causing abrupt shifts in data distribution and the update rates of model parameters. Traditional incremental learning relies on batch updates within fixed time windows, which inadequately captures instantaneous transitions in carbon emission patterns triggered by events like traffic restrictions or hurricane disasters. As evidenced by (Zhao and Li, 2024), the delay for models to restore steady-state predictions in such cases significantly exceeds practical regulatory requirements. For instance, in traffic restriction scenarios, road network flow patterns typically undergo abrupt changes within 15 minutes after policy implementation. However, mutation detection methods based on statistical hypothesis testing require accumulating sufficient sample sizes, resulting in response delays exceeding 30 minutes—a critical bottleneck that severely undermines the timeliness of real-time carbon emission simulations (Xiang, 2023). This highlights the urgent need for lightweight anomaly detection algorithms with adaptive thresholding and event-triggered parameter updating to bridge the gap between abrupt reality shifts and model adaptability.

Existing methods struggle to balance parameter update efficiency and knowledge retention under abrupt scenarios. While Elastic Weight Consolidation (EWC) mitigates catastrophic forgetting, its rigid preservation of historical patterns impedes adaptation to sudden shifts, resulting in over 40% higher fitting errors for new regulatory policies compared to baseline approaches (Yang et al., 2024). Meta-learning accelerates model reconfiguration through time-aware meta-parameters but suffers degraded generalization when historical analogs are absent, as its performance hinges on high-quality meta-task priors (Zhao and Li, 2024). Federated learning enables multi-node collaboration, yet fixed aggregation cycles (e.g., 6-hour intervals) clash with second-level response requirements for emergencies like grid failures, failing to meet real-time demands (Wen and Cao, 2020). These limitations reveal a systemic tension between preserving operational stability and enabling rapid adaptability—a gap exacerbated by the absence of frameworks that dynamically prioritize abrupt feature shifts, selectively replay critical memory traces, and decouple global consensus from localized emergency responses in carbon emission prediction systems.

4. Forward direction

The Hybrid Architecture Meta-Learning (HAML) framework, integrating Model-Agnostic Meta-Learning (MAML) with hierarchical networks, addresses dynamic multi-process coupling and few-shot abrupt scenario modeling in process industries. By enabling cross-task knowledge transfer through shared meta-parameters, HAML reduces parameter counts by 30% and accelerates convergence by 40% in cross-process adaptations like coking-steelmaking workflows (Wen and Cao, 2020). However, insufficient meta-feature encoding causes error surges when transferring vibration features from thermal power systems to chemical reactors, exposing cross-domain generalization flaws (Yan et al., 2021). Key contradictions in current methods include: (1) hierarchical meta-learning's reliance on expert-defined layers, which fails to autonomously adapt to sudden topological shifts (e.g., grid collapses) (Zhao and Li, 2024); (2) federated meta-learning's meta-gradient bias accumulation due to privacy constraints, distorting cross-regional carbon prediction knowledge beyond industrial thresholds (Yang et al., 2024); and (3) physics-guided methods' over-dependence on prior knowledge, leading to 25% higher text encoding distortion in multi-modal equipment modeling compared to purely data-driven approaches (Zhang et al., 2023). Lightweight solutions introduce new challenges: dynamic pruning triggers exponential meta-feature loss with task complexity, and asynchronous federated mechanisms—while reducing communication overhead—cause parameter update delays conflicting with second-level response needs, resulting in 30% threshold violations in real-time policy-shift predictions (Wang et al., 2015). Breakthroughs require resolving heterogeneous feature alignment and dynamic topology representation, which are pivotal for building adaptive carbon prediction systems capable of reconciling domain specificity, computational efficiency, and real-time industrial adaptability.

The unintended side effects of improvement strategies further constrain technical practicality. Data residual correction introduces long-term overfitting (Yang et al., 2024), while adjoint equation solving exhibits insufficient generalization due to sensitivity to industrial noise (Zhang et al., 2023). Current efforts must overcome theoretical bottlenecks in differential geometric adaptation and multi-scale coupling to establish physically credible carbon models. These challenges demand interdisciplinary innovations that rigorously reconcile data-driven corrections with domain-specific constraints, while developing noise-robust optimization frameworks and topology-aware regularization mechanisms to balance model flexibility with industrial deployability.

Digital twin technology drives innovation in carbon emission prediction for process industries through a "data-mechanism" dual-driven paradigm, establishing dynamic physical-virtual mappings to tackle multi-process coupling and cross-modal fusion challenges. By integrating BIM, IoT, and knowledge graphs, it achieves semantic alignment of heterogeneous data: industrial ontology mapping encodes equipment attributes and thermodynamic parameters into temporal feature vectors, resolving scale mismatches between structured and unstructured data. Hierarchical graph neural networks (GNNs) model "process-equipment" interactions for real-time carbon flow tracking, while gating mechanisms adaptively regulate cross-process weights to enhance long-range dependency modeling. Differentiable frameworks transform domain-specific equations (e.g., mass conservation) into loss functions, balancing physics-informed constraints with data-driven flexibility without relying on expert priors. Temporal alignment layers (TALs) fuse multi-frequency data via bilinear interpolation, synchronizing real-time sensor streams with manual inspections to capture abrupt emission spikes during operational transitions. Validated in steel coking and chemical reactor scenarios, this approach enables granular carbon tracing from equipment-level to system-wide emissions, offering a closed-loop virtual-real interaction framework to accelerate low-carbon transformation in energy-intensive industries.

Urban carbon emission abrupt scenario simulation faces challenges from dynamic pattern shifts induced by policy interventions and extreme events. Traditional models fail to capture sudden disturbance trajectories due to parameter rigidity and batch processing mechanisms, leading to persistent prediction drift (Zhao and Li, 2024). The meta-learning framework dynamically adjusts LSTM weights through time-aware meta-parameters, achieving minute-level model reconfiguration and reducing error recovery cycles by 70% compared to conventional methods (Zhao and Li, 2024). Federated meta-learning (FedMeta) decouples global meta-knowledge from local parameters, enabling cross-regional knowledge transfer while alleviating data scarcity pressures in new urban zones (60% reduction in data requirements) (Yang et al., 2024). Continuous-time modeling breaks discrete time-step constraints: Neural ODEs construct continuous carbon emission evolution trajectories, accurately capturing grid collapse-induced fluctuations during hurricanes (45% lower prediction error vs. traditional LSTMs) (Xiang, 2023), while adaptive step-size algorithms balance trajectory continuity and computational efficiency (35% lower computational load) (Xiang, 2023). Causal inference techniques differentiate policy impacts (e.g., carbon quota adjustments) from market volatility via structural equation modeling, reducing misjudgment rates by 50% compared to statistical approaches (Zhao and Li, 2024). The lightweight Mobile-Transformer architecture compresses parameters to 30% of traditional models, enabling millisecond-level city-wide emission responses (edge-device inference latency $<$50 ms) (Zhao and Li, 2024). This framework has demonstrated dynamic adaptability in scenarios like sudden traffic restrictions in the Yangtze River Delta (prediction delay $<$2 minutes) and typhoon disasters in the Greater Bay Area (error recovery time shortened to 15 minutes), proving its efficacy in real-world urban carbon governance under extreme conditions.

5. Conclusions

This study pioneers a carbon emission prediction framework through three theoretical breakthroughs. First, a “data-model-scenario” triadic framework unifies heterogeneous data alignment, physics-constrained dynamic modeling, and cross-scenario generalization, addressing fragmented analytical approaches. Second, a hybrid physics-data synergy integrates thermodynamics laws with adaptive hierarchical graph neural networks (GNNs) to simulate cascading carbon interactions in industrial ecosystems. Third, a privacy-preserving cross-regional paradigm bridges localized data silos and global decarbonization goals via federated learning-enhanced digital twins. Practically, the work identifies critical deployment barriers—such as quadratic memory scaling in industrial graph attention mechanisms and phase deviations in dynamic coupling models—while proposing lightweight architectures to balance computational scalability (e.g., edge deployment) and real-time calibration accuracy. By resolving tensions between thermodynamic fidelity and data-driven adaptability, this research establishes a scalable blueprint for carbon-neutral transitions in energy-intensive industries, harmonizing theoretical rigor with engineering pragmatism.

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