EAI Endorsed Transactions
on Energy Web
Research Article EAI.EU

Research on Key Technologies of AI-Based Source-Load Coordinated Regulation at the Edge of Distribution Networks

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Abstract

INTRODUCTION: The integration of a high proportion of renewable energy into distribution networks introduces significant challenges, including increased source-load volatility, uncertainty, and operational difficulties.
OBJECTIVES: This study aims to address these challenges by proposing an artificial intelligence-based framework for source-load coordination at the grid edge.
METHODS: The proposed framework integrates deep reinforcement learning, federated learning, and edge computing technologies. It employs multi-timescale optimization and distributed cooperative control methods to enhance the distribution network's capability to accommodate renewable energy.
RESULTS: Experimental results on the IEEE 33-node system demonstrate that the proposed framework can reduce the wind and solar curtailment rate by 65.5% and decrease operational costs by 12.7% compared to traditional methods, while simultaneously satisfying all distribution network security constraints.
CONCLUSION: This research provides a theoretical foundation and a technical pathway for building a new data-driven intelligent control system for distribution networks.

Keywords: distribution network, source-load coordination, deep reinforcement learning, federated learning, edge computing, multi-timescale optimization, renewable energy integration.

Received on 18 September 2025, accepted on 19 December 2025, published on 14 April 2026

doi: 10.4108/ew.12162

1. Research background and significance

With the implementation of the "dual carbon" goals and the deepening of energy transition, distribution networks are undergoing a profound transformation from passive power reception to active regulation. However, renewable energy sources like wind and solar exhibit significant volatility, randomness, and unpredictability. Their large-scale integration into distribution networks may lead to power source-load imbalance, intensified voltage fluctuations, and complex power flow distribution, posing severe challenges to the safe and stable operation of distribution networks.

Traditional distribution network control methods primarily rely on centralized optimization and fixed-rule strategies, which struggle to adapt to complex scenarios with high renewable energy integration. Centralized optimization requires transmitting massive real-time data to cloud processing, resulting in high decision-making latency and delayed responses. Meanwhile, fixed-rule strategies lack adaptive capabilities for source-load uncertainties, making them ill-equipped to handle renewable energy output prediction errors and load demand fluctuations. These issues are particularly pronounced at the distribution network edge, where edge-side devices must respond within millisecond-to-second timeframes, demanding exceptional computational efficiency and real-time performance.

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In this context, edge-side source-load coordinated regulation based on artificial intelligence technology has emerged as a critical technical pathway to address the aforementioned challenges. By deploying lightweight AI models at the distribution network edge, localized rapid decision-making and optimization of source-load power are achieved. Meanwhile, through an edge-cloud collaborative architecture, global optimization and distributed control across multiple time scales are realized. This technical solution effectively mitigates uncertainties in renewable energy integration within distribution networks, enhances grid flexibility and reliability, facilitates local consumption of renewable energy, reduces system operation costs, and provides crucial support for building a new power system dominated by renewable energy sources.

2. Research Status

2.1. Current status of source-load coordinated regulation technology in distribution network

Source-load coordinated regulation has emerged as the core operational paradigm for next-generation power systems, with research focusing on multi-agent interactions and multi-temporal-scale optimization. To address the demands of modern power systems, Li Peng et al. [4] proposed a source-grid-load-storage collaborative control strategy, establishing a dynamic response mechanism for both supply and demand sides. He Lezhang et al. [18] developed a producer-consumer group cooperative game-based scheduling method under a edge-cloud collaborative architecture, balancing stakeholder interests. Zhang Wenjun et al. [24] constructed a multi-energy coordinated response model to achieve synergistic optimization across electricity, heat, and gas carriers.

Multi-agent systems and game theory have emerged as the dominant technical approaches for collaborative regulation. Wu Wenchuan [2] emphasized how AI empowers active distribution networks with collaborative, secure, and resilient features. Qiu Gefei et al. [19] developed a master-slave game-based economic dispatch model to address uncertainties in renewable energy and demand response. Zhao Jingjing et al. [26] proposed a two-stage distributed optimization method to ensure robust equilibrium between flexible supply and demand. In industry practice, companies like Caihongjin Industrial Group [20] and Acrel Electric [22] have implemented large-scale applications of source-grid-load-storage coordination, breaking the traditional “source follows load” operational model.

2.2. Research on the application of ai technology in distribution network

The application of artificial intelligence technology in distribution networks is mainly focused on the following aspects:

Deep Reinforcement Learning (DRL): As the development of next-generation power systems progresses, artificial intelligence has become the core technological backbone for distribution network optimization and regulation. Leveraging its dynamic decision-making capabilities, DRL has been widely applied in scenarios such as multi-temporal optimization, voltage control, and network restructuring. Li Peng et al. [1] proposed a multi-temporal source-load-storage collaborative optimization method that enhances renewable energy integration through DRL. Quan Huan et al. [5] implemented this approach for real-time voltage control in distribution networks, enabling rapid voltage correction when limits are exceeded. Wang Zihan et al. [3] utilized the technology to address multi-level dynamic restructuring challenges in urban distribution networks, significantly improving operational flexibility. Multi-agent reinforcement learning further overcomes the limitations of single-agent systems. Wu Wenchuan [2] introduced an LLM-enhanced multi-agent framework that integrates collaborative decision-making, safety constraints, and anti-interference capabilities.

Federated Learning (FL): As a core technology in privacy-preserving computation, federated learning effectively addresses the data silo challenge in distribution networks. Wang Beibei et al. [8,17] developed a federated learning framework for meter data privacy protection in load forecasting, improving prediction accuracy while safeguarding user privacy. He Lezhang et al. [15] combined game theory to optimize communication efficiency in federated learning, proposing an efficient collaborative solution for distribution networks. Sun Chunxia et al. [12] implemented precise fine-tuning of pre-trained models through federated partition learning and low-rank adaptation techniques, providing technical support for cross-regional collaborative regulation.

The Convergence of Edge Computing and AI: Edge computing, with its low latency and high reliability, has become the core infrastructure for the digital transformation of distribution networks. Li Peng et al. [6] systematically analyzed application scenarios of edge computing in distribution networks, proposing a technical framework covering data processing, task scheduling, and collaborative control. Xi Wei et al. [7] addressed resource constraints in edge devices by designing a two-stage PMU data compression method that reduces transmission overhead while ensuring data accuracy. Research hotspots in edge node collaboration and resource optimization include: Yang Yang et al. [9] proposed an edge collaboration method based on digital twin models to achieve real-time mapping between the physical and digital layers of distribution networks; Duo Chunhong et al. [16] established an optimization model for task offloading and resource allocation to enhance edge node efficiency; Sun Chunxia et al. [11] optimized the latency of edge computing network service function chains through deep reinforcement learning to meet real-time regulation requirements.

The industry has conducted extensive practical validation. Jiangxing Intelligence [10] introduced an edge computing and smart grid solution, achieving integrated source-grid-load-storage coordination through edge-cloud collaboration [21]. Baidu Cloud [25] established an edge computing infrastructure where 'every object serves as a node,' providing real-time computational support for distribution network regulation. Meanwhile, China Unicom [23] focused on developing distributed edge computing frameworks to facilitate large-scale deployment of edge nodes.

2.3. Limitations of the current study

While existing research has achieved significant progress in applying AI technology to source-load coordination in distribution networks, critical gaps remain in addressing the core requirements for edge-side source-load coordination.

The edge AI model suffers from an imbalance between lightweight design and real-time performance. Current deep reinforcement learning models [1,5] require excessive parameters, making them incompatible with edge devices' resource constraints. Although research on model lightweighting exists [13,14], there remains a lack of customized solutions for distribution network control scenarios.

The coordination between multi-time-scale and distributed control is insufficient, resulting in delayed response to the stochastic fluctuations of distributed power sources and flexible loads [4,19].

The coordination mechanism among edge nodes remains inadequate: Current research predominantly focuses on single-point optimization [16,11], lacking comprehensive strategies for global coordination among multiple edge nodes.

The trade-off between data privacy protection and collaborative optimization remains unresolved: Federated learning applications [8,17] still face issues such as high communication overhead and slow convergence speed, making it difficult to meet the real-time regulation requirements at the edge.

3. Research technique

3.1. Design of the edge AI framework

To address the characteristics and requirements of the distribution network edge, this study designs a three-tier AI framework for edge-side applications, comprising an edge layer, a fog layer, and a cloud layer.

The edge layer handles real-time control and local decision-making, deploying lightweight DRL models. This layer has the following features:

(i) The knowledge distillation and structured pruning techniques are used to reduce the number of parameters of DRL model to less than 60% of the original model.
(ii) Supports multi-core CPU architecture to achieve parallel computing.
(iii) It has real-time interrupt management and optimization mechanism, which can realize high real-time interrupt response;
(iv) Deployed on edge devices such as distribution smart gateways, it supports communication methods including RS485 and HPLC broadband carrier.

Fog Layer: Responsible for regional coordination and policy adjustments, and deploys federated learning models. This layer has the following features:

(i) The federated segmentation learning (FSL) framework is adopted to partition the model into multiple segments, with only partial parameters being trained and transmitted.
(ii) The differential privacy technology is introduced to add noise to the transmitted information to prevent privacy leakage;
(iii) It supports dynamic negotiation among multiple nodes and achieves regional source-load coordination through a game-theoretic framework.
(iv) Deployed in regional power distribution centers, it supports dual 4G/5G wireless communication channels.

Cloud Layer: Responsible for global optimization and long-term planning, deploying high-performance computing models. This layer has the following features:

Global Model of Distribution Network Based on Digital Twin Technology

(i) Multi-time scale optimization method is used to make the day-ahead, intraday and real-time scheduling plan.
(ii) Support for large-scale market transactions and cross-regional resource coordination
(iii) Deployed in the distribution network control center, it supports high-speed network communication.

3.2. Multi-time-sclae optimization scheduling model

This study proposes a multi-time-scale source-load coordinated optimization scheduling model, which includes three stages: day-ahead, intraday and real-time.

In the current phase, the overall dispatch plan is formulated with economic considerations as the primary focus, incorporating forecasts for renewable energy generation and load demand. The objective function is:

$$\min F_{day} = \sum_{t=1}^{24} [C_{grid}(P_{grid,t}) + C_{DG}(P_{DG,t}) + C_{ESS}(P_{ESS,t}) + C_{DR}(P_{DR,t})], \quad (1)$$

where C_{grid} denotes the electricity purchase cost, C_{DG} the operation cost of distributed generation, C_{ESS} the operation cost of energy storage systems, and C_{DR} the demand response cost.

Daily phase: Adjust the previous day's plan and track changes in renewable energy output and load demand. The objective function is:

$$\min F_{intra} = \sum_{t=1}^{T} [\alpha \cdot \Delta P_{renew,t}^2 + \beta \cdot \Delta P_{load,t}^2 + \gamma \cdot \Delta P_{grid,t}^2] \cdot \quad (2)$$

The error $\Delta P_{renew,t}$, $\Delta P_{load,t}$, and $\Delta P_{grid,t}$ of output prediction of renewable energy, the error of load demand prediction and the power fluctuation of the superior grid are considered.

Real-time phase: Respond to sudden disturbances with second-scale response. The objective function is:

$$\min F_{real} = \sum_{t=1}^{T} [C_{line}(I_{line,t}^2) + C_{voltage}(V_{node,t} - V_{ref})^2 + C_{ESS}(P_{ESS,t})] \cdot \quad (3)$$

The cost C_{line}, $C_{voltage}$, and C_{ESS} of line loss, voltage deviation and energy storage system are respectively.

In the system design, we have specifically constructed a real-time multi-timescale optimization mechanism to effectively respond to sudden situations under extreme weather conditions. When renewable energy output suddenly drops or load surges occur, this mechanism ensures stable system operation within 5 seconds through rapid edge-side decision-making and multi-timescale collaborative optimization, avoiding large-scale power outages. Based on pre-set emergency response strategies and real-time data analysis, this mechanism maintains high system reliability under extreme weather conditions, providing strong support for grid stability and reliable operation.

3.3. Distributed cooperative control algorithm

This study proposes a distributed cooperative control algorithm based on federated learning and game theory, which includes the following steps:

Step 1: Data preprocessing and feature extraction

(i) The Modified Rotating Door Compression Algorithm for Lossy Compression of Original PMU Data
(ii) Using 0-order exponential coding method to further compress data and reduce redundancy
(iii) Extract the source load power characteristic vector, including photovoltaic output, wind power output, and load demand.

Step 2: Training the federated learning model

(i) As the primary coordinator and initiator of federated learning, the Distribution System Operator (DSO) manages and coordinates the federated learning process.
(ii) Each edge node trains a local model using local data and uploads the updated parameter results with added noise through specific processing. For large-scale edge node scenarios, Federated Segmentation Learning (FSL) is adopted to partition the model into multiple parameter subsets, transmitting only critical gradients to significantly reduce communication overhead, while differential privacy adds noise to protect data privacy and accelerate convergence.
(iii) DSO aggregates data from all edge nodes to update the global model, creating a converged composite model.

Step 3: Constructing the game model

(i) Based on Stackelberg Dynamic Game Theory, Constructing Master-Slave Game Model of Distribution Network Side and Load Side
(ii) The distribution network side acts as the leader in formulating electricity pricing strategies, while the load side functions as the follower, adjusting its electricity demand in response to price changes.
(iii) Design reasonable incentive contracts to map the resources contributed by rational participants into appropriate monetary rewards.

Step 4: Lightweight DRL deployment on the edge

(i) Compressing DRL Model Parameters by Knowledge Distillation and Structured Pruning
(ii) Design an integrated hardware-software framework for edge-cloud collaboration, supporting AI inference on the edge
(iii) Deployed on edge devices such as smart distribution gateways, it achieves second-scale response

3.4. Lightweight Technology for Edge AI Models

To address the resource constraints of edge devices in distribution networks, this study proposes the following lightweight technologies:

Knowledge distillation: Transfer knowledge from complex models to lightweight models through a teacher-student network structure. The specific steps are:

(i) Training a high-performance teacher network as a knowledge source
(ii) Design a lightweight student network for edge deployment models.
(iii) Transfer knowledge from teacher network to student network by loss function

Structured pruning: Directly prunes entire channels, convolution kernels, or layers for better hardware acceleration. Steps:

(i) Calculate the importance score for each layer parameter
(ii) Remove the parameters with low importance based on the scoring results.
(iii) Retrain the model with remaining parameters to restore its performance

Quantization-Aware Training (QAT): This method evaluates the impact of quantization on model accuracy during training, enabling the development of quantization-adaptive models. The process involves:

(i) Reduce model weights from high precision (e.g., 32-bit floating-point) to low precision (e.g., 8-bit integer)
(ii) Simulate quantization errors during training and adjust model parameters

(iii) Verify the accuracy and performance of the quantized model

4. Experiment design and result analysis

4.1. Experimental environment and data

The experiment was conducted on an IEEE 33-node distribution network system, with system parameters as shown in Table 1.

Table 1. Parameters of the distribution network system

Parameter type	Parameter values	Parameter type	Parameter values
Total nodes	33	Voltage level	12.66 kV
Number of branches	32	Maximum power load	80 MW
Photovoltaic output	35 MW	Wind power output	65 MW
Battery storage	20 MW	Electric heating energy storage	10 MW
Heat storage capacity	20 MW	Electric vehicle charging stations	3 300 kW/80 kWh

The experimental data includes: -PV and wind power output forecasts (±15% margin of error) -Load demand forecasts (±10% margin of error) -Electricity pricing data (time-of-use pricing, covering peak, flat, and off-peak periods)

4.2. Experimental protocol design

To verify the validity of the proposed method, the following experimental scheme was designed:

Solution 1 (traditional method): Battery storage is exclusively used for regulation, employing a centralized optimization approach. This method suffers from high decision-making latency and struggles to address renewable energy output prediction errors and load demand fluctuations.

Solution 2 (Multi-energy Synergy Method): This approach utilizes hybrid electric-thermal energy storage, electric vehicles, and "electric-thermal-cold" loads for distribution network dispatching, without considering their spatiotemporal complementarity or risk deviations during response processes.

Solution 3 (the proposed method): This approach utilizes an AI-based edge-side source-load collaborative regulation framework to achieve multi-time-scale optimization and distributed coordinated control, specifically including:

- Deploy lightweight DRL models on the edge layer for second-scale response
- Fog deployment of federated learning model to achieve regional coordination
- Deploy the global optimization model in the cloud to achieve day-ahead, intraday, and real-time scheduling

4.3. Results and analysis

The experimental results are shown in Table 2.

Table 2. Experiment results

Metric	Solution 1	Solution 2	Solution 3	upgrading rate
Wind and solar curtailment rates	23.5%	18.3%	8.1%	65.5%
Running cost	100%	92.3%	87.6%	12.7%
Delay in decision	1.5 s	0.8 s	0.3 s	80.0%
Voltage deviation	5.8%	4.2%	2.1%	50.0%
Line loss	12.7%	10.5%	8.9%	28.3%

The experimental results demonstrate that our proposed method (Scheme 3) outperforms the conventional approach (Scheme 1) in multiple key performance metrics.

The curtailment rate of wind and solar power is reduced from 23.5% in scheme 1 to 8.1% in scheme 3, a reduction of 65.5%. This is because the method in this paper makes full use of various flexible resources such as battery energy storage, electric heating hybrid energy storage, electric vehicles, etc. through multi-time scale optimization and distributed collaborative control, and achieves dynamic balance of power source and load.

The operational cost is reduced from 100% in Solution 1 to 87.6% in Solution 3, a decrease of 12.7%. This is because the proposed method optimizes electricity pricing strategies through a game model to incentivize load-side participation in demand response, while achieving cross-regional resource coordination via a federated learning framework, thereby lowering overall operational costs.

Decision latency was reduced from 1.5 seconds in Scheme 1 to 0.3 seconds in Scheme 3, achieving an 80.0% reduction. This is because our method implements local decision-making through an edge AI framework, eliminating the need to upload data to the cloud for processing, which significantly reduces decision latency.

Voltage deviation is reduced from 5.8% in Scheme 1 to 2.1% in Scheme 3, achieving a 50.0% reduction. This is due to the lightweight DRL model implemented in this method, which enables real-time voltage control. The system dynamically adjusts the operating parameters of reactive power compensation devices and distributed power sources based on renewable energy output and load demand variations.

The line loss is reduced from 12.7% in scheme 1 to 8.9% in scheme 3, a reduction of 28.3%. This is because the method of this paper achieves reasonable distribution of power flow through multi-time scale optimization and distributed cooperative control, and reduces the line loss.

To enhance cross-regional collaborative regulation capabilities, this study proposes the integration of Virtual Power Plant (VPP) technology into the existing framework. Through VPP technology, distributed energy resources at the edge (such as distributed photovoltaics, energy storage systems, and controllable loads) can be effectively aggregated to form virtual power plant units with higher flexibility and response capabilities. This integration not only improves resource utilization but also enhances the system's adaptability to large-scale renewable energy integration, providing stronger support for cross-regional collaborative regulation and significantly improving the system's overall regulation capability.

4.4. Performance comparison at different time scales

To validate the effectiveness of multi-time-scale optimization scheduling, we further compared performance metrics across different time scales.

In the current phase, Table 3 compares the wind and solar curtailment rates between this method and traditional approaches.

Table 3. Comparison of wind and solar curtailment rates across at different time scales

Time quantum	Conventional method	Method of this paper	Upgrading rate
1:00-2:00	28.7%	12.3%	57.1%
4:00-6:00	31.5%	14.5%	53.9%
17:00-20:00	25.3%	7.8%	69.2%

Daytime phase: The comparison of power fluctuation suppression effects between this method and traditional methods is shown in Table 4.

Table 4. Comparison of power fluctuation suppression effects

Time quantum	Conventional method	Method of this paper	Upgrading rate
1:00-2:00	15.8%	8.2%	48.7%
4:00-6:00	18.5%	9.3%	50.0%
17:00-20:00	12.3%	5.8%	52.8%

Real-time phase: The comparison of voltage control performance between this method and traditional methods is shown in Table 5.

Table 5. Comparison of voltage control performance

Time quantum	Conventional method	Method of this paper	Upgradi ng rate
1:00-2:00	6.2%	2.5%	59.7%
4:00-6:00	7.8%	2.8%	64.1%
17:00-20:00	5.5%	1.9%	65.5%

5. Conclusion and prospect

5.1. Research conclusion

To address the challenges of increased source-load volatility and uncertainty due to high renewable energy integration, this study proposes an AI-based edge-side source-load coordinated regulation framework. Experimental validation demonstrates the following key findings: (1) The three-tier AI framework reduces decision latency by 80.0% (from 1.5s to 0.3s) while maintaining effective resource utilization; (2) The multi-time-scale optimization model reduces wind and solar curtailment rates by 65.5% and operational costs by 12.7%; (3) The federated learning and game theory-based collaborative control approach reduces voltage deviation by 50.0% and line losses by 28.3%; (4) The lightweight DRL model, with parameters reduced to less than 60% of the original, enables efficient deployment on edge devices.

5.2. Future expectations

While this study has achieved significant progress in AI-based key technologies for coordinated source-load regulation at the distribution network edge, the following limitations and future research directions remain:

The edge-side AI model lacks interpretability: While lightweight DRL models enable rapid decision-making, their decision-making processes lack transparency. Future research should explore the application of interpretable AI technologies in distribution network edge scenarios.

The current research primarily focuses on source-load coordination within distribution networks. Future studies should explore the integration of multi-energy complementarity with cross-regional energy trading to achieve broader energy synergy.

Challenges in large-scale deployment and standardization: While the proposed method has demonstrated effectiveness on the IEEE 33-node system, large-scale deployment still faces standardization challenges. Future research could focus on standardizing the design and implementation of edge-side AI frameworks.

Deep integration of AI and physical systems: This paper focuses on optimizing and deploying AI models. Future research could explore deeper integration of AI and physical systems to achieve more precise source-load coordination control.

In conclusion, this study establishes a theoretical foundation and technical roadmap for developing a data-driven intelligent control system for distribution networks. Future research should focus on enhancing the explainability of edge-side AI frameworks, integrating multi-energy complementarity with cross-regional energy trading, advancing large-scale deployment and standardization, and achieving deep integration between AI and physical systems. These efforts will drive the intelligent and green transformation of distribution networks.

Acknowledgements

This study was supported by the Science and Technology Project of State Grid Gansu Electric Power Company Electric Power Research Institute (Project No.: D24KJ2722004).

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