Theory and Practice of Science and Technology
2025, VOL. 6, NO. 9, 168-174
DOI: 10.47297/taposatWSP2633-456933.20250609

Review of Modeling and Optimization for Low-Carbon Integrated Energy Systems Considering Electric Vehicles and Transportation Networks

Yiming Zhang

School of Electrical and Information Engineering, Tianjin University, Tianjin, 300072, China

ABSTRACT
The integration of energy and transportation systems (IETS) is essential for low-carbon development. With the rapid growth of electric vehicles (EV), charging infrastructure couples energy and traffic flows, introducing uncertainties but also enhancing flexibility. This paper reviews recent progress in IETS modeling and optimization, emphasizing coordinated scheduling, regulatory mechanisms, and multi-participant interaction. Game-theoretic models are highlighted for capturing competitive and cooperative behaviors among system operators, while carbon trading and price-based coordination are examined as effective tools for aligning incentives in system operating.

KEYWORDS
Integrated energy system; Transportation network; Electric vehicle; Collaborative optimization; Cyber-physical system

1 Introduction

Facing severe environmental challenges, "carbon peaking and carbon neutrality" have become the core of China's energy strategy. The 14th Five-Year Plan calls for accelerating the construction of new power systems and promoting low-carbon and intelligent upgrades. By 2025, flexible resources should reach about 24% and demand response 3%–5% of peak load, with a modern energy system essentially built by 2035. It also stresses enhancing load flexibility, deepening Vehicle to Grid (V2G) interaction, and promoting coordinated electric vehicles (EV) -charging development with bidirectional energy and information exchange [1].

Building a new power system dominated by renewable energy is fundamental to achieving the dual-carbon goals. By 2025, renewables will account for over 56% of capacity, and by 2030 are expected to exceed 70% [2]. High penetration of wind and solar may cause severe source–load mismatches, leading to reverse power flow, congestion, and overvoltage [3]. Thus, tapping demand-side flexibility is essential for secure operation.

Electricity, heat, and transportation are the top three carbon-emitting sectors and key targets for reduction. EVs, as controllable loads and mobile storage, can participate in grid regulation and are also critical for joint decarbonization of transport and power. By 2030, China's EV fleet will approach 100 million, with battery capacity exceeding 40 billion kWh, over 60% of average daily wind-solar generation, and a smart and efficient charging system will be established [4]. Growing electrification will reshape traffic and power flows, deepening "driver-vehicle-charger-road-network (DVCRN)" coupling, as V2G as well as V2V, V2N, and V2X will advance rapidly [5].

With transportation-information networks, EV travel and charging couple power and traffic flows via chargers, forming the Integrated Energy and Transportation System (IETS). The multi-dimensional uncertainties of EVs affect grid load distribution and flexibility, while EVs' storage and interactive features mean travel paths, dwell times, and charging needs directly influence load, and price signals, grid limits, and carbon costs feed back into charging and travel decisions. Hence, unified modeling and co-optimization of power and transportation are required to improve system coordination and emission reduction.

The Integrated Energy System (IES) couples electricity, heat, cooling, gas, and hydrogen to exploit complementarities, improving efficiency and economics, and is a core part of the new power system [6]. It features multi-energy, primary-secondary, and cyber-physical integration. On the user side, distributed renewables, storage, and EVs can jointly form regional low-carbon IES, enhancing renewable absorption and overall efficiency. Energy-information co-optimization has become a new paradigm, and integrated energy stations with chargers highlight the need for multi-network coordination of transport, energy, and information, bringing new challenges and opportunities.

This review will systematically summarize models and co-optimization methods for IES and transportation networks with EV participation. It also considers carbon emission trading and multi-agent games in optimization to support low-carbon and flexible operation of the new power system.

2 Coupled scenarios of transportation and energy systems

2.1 IETS architecture

Transportation–energy systems exist in various forms [4-5,7]. This review focuses on the IETS, a highly complex framework that combines transportation–power coupling, cyber–physical fusion, and multi-energy integration, involving multiple flows and multi-agent interactions. Building integrated IETS offers several advantages: (1) fully exploiting system flexibility by optimizing the spatiotemporal distribution of EVs to expand the SOC range; (2) improving traffic-flow regulation efficiency through complementary measures, e.g., price control and congestion charges; (3) maximizing overall benefits of energy and transportation networks by balancing low-carbon transition with traffic efficiency, and by optimizing EV routing and charging location planning [8].

The transportation network (TN), as the carrier of EVs, is coupled with the energy network through charging piles. Locating charging piles within integrated energy stations can improve energy utilization and enhance flexibility [9]. Thus, IETS can be understood as the coupling of multiple physical networks i.e. TN, power distribution networks (PDN), natural gas pipelines, and heating networks—while diverse energies in IES are coupled through devices like CHP and P2G. The coupling nodes between EVs and IES are realized via the PDN, and most studies focus on the integration of PDN and TN [3-5,8]. This paper adopts that framework while further extending to the participation of integrated energy in IETS.

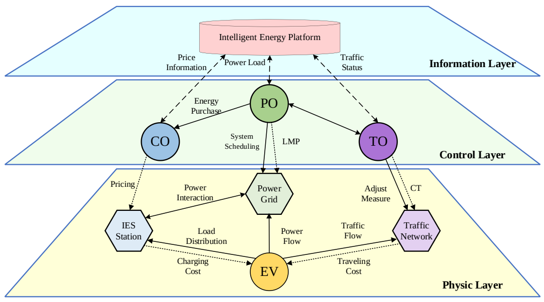

Figure 1 Architecture of IETS

The overall IETS architecture consists of three layers: physical, information, and decision-control. The physical layer includes the PDN, integrated energy providers, transportation networks, and charging infrastructure, with charging piles and energy stations serving as key nodes where electricity is converted into mobility. The information layer, composed of vehicular networks, traffic information platforms, and energy management systems, enables real-time monitoring and data exchange to support the physical layer. The decision-control layer involves power system operators, transportation authorities, charging service providers, and policymakers, who regulate the system through incentives mechanisms. Within this multi-layer framework, energy flow, traffic flow, and information flow are tightly coupled.

The system involves multi-agent interactions. EV load forecasting depends on data sharing among transportation authorities, power grids, and operators, while the planning and optimization of integrated energy stations and EV behavior also require coordination among multiple participants. Map apps and automakers are responsible for route optimization, charging-point recommendations, and vehicle–grid data interaction. Charging operators improve revenue through dynamic pricing while also providing ancillary services. Transportation authorities regulate traffic flows and enhance road network efficiency. Power, gas, and heating enterprises ensure energy supply, optimize network flows, and facilitate renewable integration [10]. These participants rely heavily on data exchange. At present, transportation departments and automakers have jointly established several new-energy big data platforms to capture travel patterns and charging preferences, supporting EV mobility analysis [3,5]. Meanwhile, strong competition and game-like interactions exist among EV charging infrastructure operators within the same region. In addition, charging operators can aggregate charging and swapping facilities to participate in electricity markets, creating both cooperative and competitive relationships with EV users and power grid operator [10].

2.2 Key technologies and challenges

2.2.1 Flexible region model and optimization

The flexible region under the coupling of drivers, vehicles, piles, traffic, and networks is a feasible approach, in which price and flow regulation can be used to optimize the spatio-temporal distribution of loads. The larger the flexible region, the broader the feasible domain for network planning and operation optimization, and the stronger the capability to approach the optimal solution. The key technologies of collaborative optimization based on the flexible region include: (1) flexibility modeling of coupled networks, (2) flexible region modeling and multi-spatio-temporal prediction based on multimodal information fusion, (3) collaborative optimization of PDNs under coupled scenarios, and (4) multi-rate hierarchical optimization of PDN–TN systems based on multi-spatio-temporal flexible regions [5].

2.2.2 Temporal differences in multi-systems

The power grid are fast systems, where grid steady-state corresponds to the slow dynamic analysis of transportation networks, while heat and gas in integrated energy systems are also slow systems. Coupled regulation must therefore consider the establishment of appropriate spatio-temporal models under different scenarios. The introduction of IES sharply increases system complexity, as it involve coupling nodes of multiple energy carriers. Moreover, heating in buildings and other flexible loads add to the complexity of constraints and power flow analysis.

2.2.3 Information and data supporting

The uncertainty of human factors represents a critical challenge for multi-network integration. The macroscopic distribution of power and traffic flows relies on the collective travel–charging decisions of massive EV users, which are essentially complex social behaviors. Analyzing EV behavior therefore requires extensive big-data support, while the regulation of information flows calls for close coordination among multiple participants.

3 Modeling of IETS

3.1 EVs traffic model

Slow charging of EVs is mainly associated with residential buildings, where the coupling with transportation networks is weak. In contrast, fast charging at public stations during trips exhibits strong coupling, as EVs link traffic flow and energy flow, requiring consideration of route and charging-location flexibility. EV decision-making can be broadly categorized into individual autonomy and collective fleet coordination. Buses and ride-hailing vehicles are amenable to platform-based centralized scheduling and thus exhibit collective rationality, unlike the stochastic behaviors of taxis and private cars. Existing studies mainly address individual decision-making [3].

Traditional approaches such as Monte Carlo simulation and queuing theory [11] based on traffic statistical data are only applicable in scenarios with low EV penetration, and they do not consider the dynamic scheduling of TN. Models based on OD probability matrices can capture travel demand but fail to account for user decision-making [4]. References [4,12] proposed the trip-chain model, which is a set of travel–parking activity state chains incorporating dimensions such as time, space, and SOC. Combined with MCS, Markov randomization, and VPR solutions, this model can better characterize the dynamic behavior of EVs.

3.2 Traffic network model

Traffic assignment (TA) is the core of traffic system modeling, used to compute TN flows from origin–destination (OD) demands. Models such as the FCLM have been widely applied to charging station planning [4]. TA models can be categorized by temporal granularity into static, semi-dynamic, and dynamic TA. STA is analogous to steady-state circuit analysis, while the others resemble distributed-parameter circuits [3]. Static models are relatively mature. Traditionally, traffic congestion has been simulated via impedance functions, e. g., the BPR and Davidson functions to describe congestion and charging queues. Extended graph-theoretic approaches with virtual links provide a unified representation of EVs and conventional vehicles, and are widely applied in IETS analysis [4]. Other models incorporate trip-chains, demand elasticity, and mixed traffic flows, offering robustness in practical analysis. Dynamic models capture traffic-flow hysteresis and are typically divided into spatio-temporal extended networks and dynamic traffic networks [13]. However, no unified dynamic model exists; the formulations often involve nonlinear complementarity and variational inequalities, making the solution computationally complex.

Queueing theory is also widely employed for charging station analysis, often by using predefined nonlinear functions such as the M/M/c/K model to estimate waiting times [8]. Reference [11] further introduced an elasticity model accounting for user decision probabilities regarding waiting.

Optimization criteria for TN are generally classified into user equilibrium (UE) and system optimal (SO). UE is more suitable for individual autonomous decision-making, whereas SO is appropriate for coordinated fleet decisions. UE assumes fully rational users with complete information, aiming for traffic flows to reach equilibrium, corresponding to Wardrop's first principle, and is widely applied in IETS studies. Stochastic user equilibrium (SUE) extends UE by modeling bounded rationality, incorporating randomness in travel demand, distance, and route choice. Mixed-UE considers the interactions between EVs and conventional vehicles. In addition, improved UE variants account for elasticity, budget constraints, environmental costs, and fault scheduling. Reference [8] provides a unified formulation framework for such extensions. SO, by contrast, minimizes the total system cost of TN operation, corresponding to Wardrop's second principle. Related formulations include network optimization models such as the Beckmann and Nesterov models [4]. Introducing congestion tolls (CT) can guide TN flows from UE toward SO, analogous to reactive power compensation in power systems [3]. Optimization can also be integrated with DTA models, forming DUE and DSO formulations [4].

3.3 Power distributing network model

The economic operation of power systems can be formulated as an optimal power flow (OPF) problem, which is generally divided into DCOPF and ACOPF. DCOPF neglects network losses and voltage drops, considers only active power flows, is convex, and can be solved efficiently, making it suitable for approximating grid constraints in coupled systems.

ACOPF, by contrast, is more appropriate for long-term planning analysis and for the calculation of locational marginal prices (LMP) with losses. However, it is a non-convex, NP-hard problem; various optimization algorithms have been proposed.

The branch flow model (BFM) directly models the relationships among branch power, current, and voltage, and is naturally compatible with radiating PDNs. BFM variables correspond directly to physical quantities, making the model more intuitive. In the context of IES, BFM is more easily linked with gas and thermal networks, and it naturally supports distributed algorithms such as ADMM and hierarchical optimization. Moreover, BFM can be readily relaxed into a convex optimization problem through SOCP relaxation, leading to the SOCR-BFM model, and can also be linearized into the linearized BFM model. The former provides higher accuracy, while the latter offers higher computational efficiency. In IETS studies, SOCR-BFM has been widely applied. Since it accounts for reactive power and bus voltages, it remains more suitable than DCOPF [4].

3.4 Integrated energy system model

As the physical carrier of the energy internet, IES enables the conversion and coupling of multiple energy carriers, including electricity, heat, gas, and hydrogen, and further involves distributed generators (DG) and EVs, making its models and constraints particularly complex. The energy hub (EH) is a widely used modeling framework for IES. Reference [6] proposed an IES architecture based on the EH as its backbone and presented a steady-state analysis paradigm for regional IES. Reference [14] applied the EH model to jointly optimize multiple IESs under carbon capture-storage scenarios.

Network optimization of IETS involves not only TN and PDN but also natural gas and district heating networks, which are coupled through integrated energy stations. Reference [15] proposed a unified energy-flow theory for electricity–heat–gas coupling. Existing studies typically incorporate power flow constraints for the electrical network, pressure and flow balance constraints for the natural gas network [9,16], as well as hydraulic and thermal models of heating and return-water networks and heat-exchange stations [17].

Within integrated energy stations, possible energy supply devices include gas boilers (GB), combined heat and power (CHP), power-to-gas (P2G), electrical chillers (EC), and absorption chillers (AC). Other components may include EVs, electrical storage (ES), photovoltaics (PV) and wind turbines (WT), thereby meeting diversified electricity – gas – heat – cooling load demands. To further support decarbonization, studies [18-20] introduced hydrogen energy, incorporating hydrogen blending retrofits for CHP and GB, as well as additional equipment including electrolyzers (EL), hydrogen storage (HS), and hydrogen fuel cells (HFC), further complexing system coupling. The modeling of IES stations must therefore account for device-level operational constraints and multi-energy balance conditions across electricity, heat, cooling, gas, and hydrogen, while dynamically adjusting outputs according to IETS network requirements.

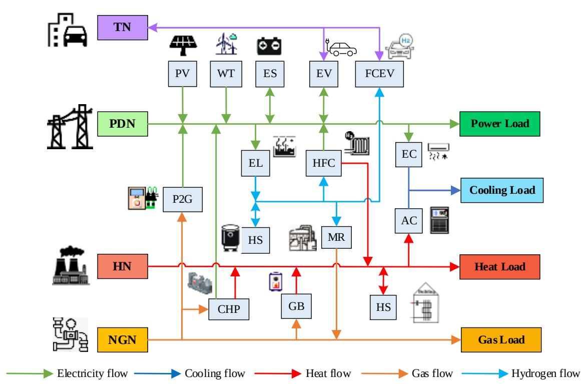

Figure 2 IES coupling with transportation network

In IES, EVs act as mobile storage, while buildings, as stationary loads, can also be modeled as flexible demand to enhance overall network regulation capability. Reference [21] proposed an equivalent R-C thermal load model for buildings; Reference [22] investigated the coordination between clusters of buildings with differentiated insulation performance and microgrid systems; Reference [17] analyzed the thermal dynamics of campus-level IES and the Stackelberg game between operators and users. When buildings are treated as virtual storage, Reference [23] presented an optimization model for scheduling across building-level microgrids considering both V2B and virtual storage. The joint optimization of campus-level IES that simultaneously considers EVs, transportation networks, and the dynamic thermal loads of buildings remains a promising research direction.

3.5 Multi-participant interaction in IETS

In IETS, multiple participants are involved, mainly including the power system operator (PO), the transportation system operator (TO), and the IES operator, which purchases energy from upper-level energy systems and supplies loads through coupling, also known as charging station operators (CO). These participants engage in competition but may also cooperate through various mechanisms.

3.5.1 Regulatory mechanisms

In the TN, the TO can influence vehicle route choices to improve traffic flow distribution through CT, adaptive signal timings, and tidal lanes measures [8]. The PO, aiming at secure and economic operation, regulates generation dispatch, network topology, and flexible load scheduling. LMP, a pricing model in the electricity spot market, is derived from OPF or SCUC and clears according to marginal cost to achieve economic dispatch. LMP has been widely applied in IETS regulation [4]. The IES operator (CO), typically targeting profit maximization, determines energy procurement plans and charging tariffs, and may employ price signals to guide EV charging demand towards a balanced allocation across stations. IETS regulation involves diverse price signals under multiple business models, including campus-level IES, virtual power plants [24], and user aggregators [17]. To ensure regulatory effectiveness, price signals generally require upper and lower bounds [3,8]. To address this, under the DVCRN framework, participants can utilize smart energy platforms to share traffic, load, and price data, facilitating coordinated siting, planning, and operational optimization.

3.5.2 Game-theoretic models

Studies on IETS typically adopt Nash equilibrium, where participants decide simultaneously, and Stackelberg competition, where leaders move first and followers respond [8]. Depending on network characteristics, congestion games, Stackelberg games, and potential games may also be applied [4]. Stackelberg games have been extensively studied: Reference [12] examined such a game between microgrid operators and user aggregators; Reference [5] summarized game models for distribution network planning based on flexibility regions; Reference [17] considered Stackelberg interactions between IES operators and flexible buildings. The cooperation−game patterns among participants can be categorized as follows: (1) PO directly interacts with EVs, either through Nash equilibrium under LMP-based pricing or Stackelberg games under retail tariffs. (2) TO engages in games with users while coordinating pricing with the PO or adopting Nash equilibrium. Reference [3] reviewed equilibrium analysis and coordinated regulation of IETS. (3) COs, particularly IES operators, are treated as independent participants, engaging in equilibrium or games with the upper-level PO while also playing games with users. Games among multiple COs, where multi-level Stackelberg games or generalized Nash equilibria are applied to represent competitive bidding [3,10]. These models also provide references for planning new charging stations.

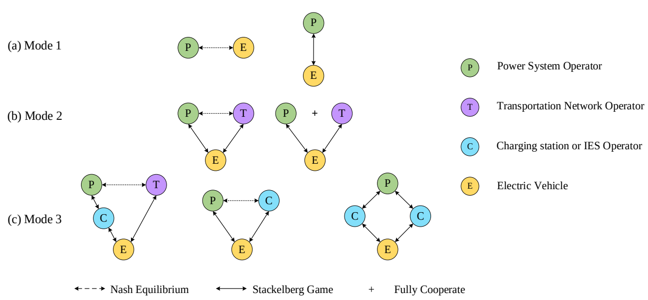

Figure 3 Game modes of IETS participants

4 Collaborative optimization

4.1 Carbon emission trading

Indicators such as carbon emissions and PV penetration are of great significance in the decarbonization process of IETS. Carbon emission trading (CET) is an effective measure introduced to further incentivize carbon reduction. Low-carbon participants can sell carbon allowances in the carbon trading market to obtain direct economic benefits, while high-carbon enterprises can purchase additional quotas to meet compliance standards. The main challenge of introducing CET lies in establishing practical carbon allowance and emission models for energy-consuming devices and equipment. References [19,25-27] introduced a step-CET to optimize IES with EV participation. Reference [12,28] constructed an integrated electricity–carbon market model by combining CET with green certificate trading (GCT).

4.2 Optimization models

4.2.1 Optimization objectives

The optimization objectives of the power system and TN are economic operation and optimal distribution of network flows. For IES, the objective is to minimize investment and operation costs, considering the operating costs of coupled devices, the cost of purchasing energy from upper-level systems, the load of the power, gas, and thermal networks, as well as the scheduling costs of DGs and flexible loads such as buildings. Under the decarbonization context, each system also needs to minimize carbon emission under CET and maximize renewable energy integration.

For the overall IETS, since multiple regulatory prices such as LMP and CT exist across systems, studies can focus on multi-participant equilibrium and game-theoretic models under the UE criterion, as well as minimizing the total social cost – – TN travel time and PDN costs [3]. In scenarios where participants have conflicting interests, bilevel optimization models [17,21] and Stackelberg games [12,17] can be applied.

4.2.2 Solution approaches

Solvers such as MATPOWER, CPLEX, and Gurobi are generally used to solve integrated power – transportation models. Simulation and modeling of transportation networks can be carried out with tools such as PTV VISSIM, SUMO, and MATSim, while traditional OD matrices can be estimated using software TransCAD [4]. Various relaxation methods have been developed to address non-convexity, such as the SOCR-BFM model for PDNs and piecewise linearization (PWL) methods for PNs. For IETS coordinated scheduling models that incorporate UE conditions, the feasible region often fails to satisfy the MFCQ, making conventional solvers prone to numerical stability issues [8]. Therefore, approaches such as Big-M approximation, iterative relaxation, conic relaxation, and variational inequalities (VI) are commonly employed. Game-theoretic models are solved using methods including piecewise linearization, fixed-point iteration, multi-agent DRL, conic relaxation, VI, and MIQP [3].

4.3 Optimization scenarios

4.3.1 Facility planning and scheduling

The siting and sizing of charging stations is a hotspot issue in IETS planning, with most studies adopting UE-based models. References [29-30] focused on the coordinated optimization of TN – PDN under the background of dynamic wireless charging (DWC) technology. Reference [18] proposed an optimization planning model for wind – solar – hydrogen IES considering stochastic EV charging. Reference [9] introduced a one-stop IES station concept that integrates electricity, cooling, heating, and gas with TN, and employed a mixed-UE modeling approach for optimization. Reference [11] presented a vehicle – grid coordinated optimization scheme incorporating V2G participation willingness and queueing theory. Reference [10] reviewed IES station planning with hydrogen fuel cell vehicle participation. In addition, studies have also examined PV and energy storage planning [4].

4.3.2 System optimal operating

The focus of system operation optimization lies in dynamic pricing. Reference [16,31] proposed IETS robust optimal scheduling methods considering multiple uncertainties in both TN and the power grid. Reference [23,32] developed an optimization scheduling model for building-level microgrids that accounts for V2B and virtual storage. Reference [33] presented an IETS regulation and optimization approach based on LMP. Reference [34] introduced elasticity coefficients and proposed a hierarchical pricing strategy. Reference [35] investigated game-theoretic optimization among different operators in ITES. Reference [12] incorporated an EV trip-chain model, while Reference [7] addressed the dynamic scheduling of TN demand and DG.

5 Conclusion

This review has summarized the current progress in modeling and optimization of IETS with EV participation. The survey highlights key challenges of coupling energy and traffic flows, integrating carbon emission constraints, and managing system uncertainties. Particular emphasis has been placed on multi-participant coordination and game-theoretic approaches, which provide effective frameworks to capture both competitive and cooperative behaviors among power, transportation, and energy service operators. By consolidating insights from diverse studies, the paper underlines that coordinated regulation and market-based mechanisms are central to improving flexibility, efficiency, and decarbonization in IETS.

Future developments are expected to move toward greater refinement, lightweight solution methods, diversified scenarios, and feasible coordination [8]. Accelerating the construction of big data integration will support a shift from individual and deterministic optimization to collective guidance and stochastic optimization [3].

References

[1] National Development and Reform Commission (NDRC) and National Energy Administration (NEA). Notice on Issuing the 14th Five-Year Plan for Modern Energy System[EB/OL]. [2025-08-01]. https://www.gov.cn/zhengce/zhengceku/2022-03/23/content_5680759.htm.

[2] Annual Development Report of China's Electric Power Industry 2025[EB/OL]. [2025-08-30]. https:/www.cec.org.cn/detail/index.html?3-347889.

[3] Sheng Y, Guo Q, Xue Y, et al. Collaborative modeling and optimization of power-transportation coupling network from cyber-physical-social perspective[J]. Automation of Electric Power Systems,2024,48(7):62-85.

[4] He K , Jia H, Mu Y, et al. A Review of Modeling Approaches for Integrated Transportation-power Energy Systems[J]. Global Energy Interconnection, 2023, 6(5): 473-489.

[5] Mu Y, Jin S, Zhao K, et al. Collaborative Planning and Operation Optimization of Distribution Networks Under Deep Coupling of Drivers, Vehicles, Piles, Traffic and Network[J]. Automation of Electric Power Systems, 2024, 48(7): 24-37.

[6] Wang W, Wang D, Jia H, et al. Review of Steady-state Analysis of Typical Regional Integrated Energy System Under the Background of Energy Internet[J]. Proceedings of the CSEE, 2016, 36(12): 3292-3306.

[7] Li L, Han Y, Li Q, et al. Multi-dimensional economy-durability optimization method for integrated energy and transportation system of net-zero energy buildings[J]. IEEE Transactions on Sustainable Energy, 2024, 15(1): 146-159.

[8] Lyu S, Chen S, Wei Z, et al. Review of Modeling, Solution and Application for Coordinated Operation of Power-Transportation Systems[J]. Automation of Electric Power Systems, 2025, 49(13): 1-15.

[9] Wang J, Hu Z, Xie S. Smart Multi-energy System Planning Considering the Traffic Scheduling[J]. Proceedings of the CSEE, 2020, 40(23): 7539-7555.

[10] Hu Z, Shao C, He F, et al. Review and Prospect of Research on Facility Planning and Optimal Operation for Coupled Power and Transportation Networks[J]. Automation of Electric Power Systems, 2022, 46(12): 3-19.

[11] Hu M, Chen S, Wei Z, et al. Research on collaborative optimization of distribution network considering Vehicle-to-Grid and elastic queuing theory [J/OL]. Zhejiang Electrical Power, 2025, 44(8): 3-14.

[12] Fu B, Ding H, Quan Y, et al. Study on Low-Carbon Economic Operation of Integrated Energy Systems in Parks Considering Electric Vehicle Travel Chain[J/OL]. Southern Power System Technology, 2025.

[13] Long J, Guo J. Review and Prospect of Dynamic Traffic Assignment Research [J]. Journal of Transportation Systems Engineering and Information Technology, 2021, 21(5): 125-138.

[14] Xu D, Hu A, Lam C S, et al. Cooperative planning of multi-energy system and carbon capture, utilization and storage[J]. IEEE Transactions on Sustainable Energy, 2024, 15(4): 2718-2732.

[15] Chen Y, Sun H, Guo Q. Energy Circuit Theory of Integrated Energy System Analysis (V): Integrated Electricity-Heat-Gas Dispatch[J]. Proceedings of the CSEE, 2020, 40(24): 7928-7937, 8230.

[16] Zhang Y, Zheng F, Shu S, et al. A Data-Driven Robust Optimization Scheduling of Coupled Electricity-Gas-Transportation Systems Considering Multiple Uncertainties[J]. Proceedings of the CSEE, 2021, 41(13): 4450-4462.

[17] Zhang G, Li J, Zhang X, et al. Coordinated Optimization of Buildings and Integrated Community Energy Systems Through a Bi-level Model Predictive Control Method with Stackelberg Game [J]. Journal of Global Energy Interconnection, 2025, 8(3): 289-298.

[18] Zhou J, Wu Y, Dong H, et al. Optimal Planning of Wind-Photovoltaic-Hydrogen Integrated Energy System Considering Random Charging of Electric Vehicles[J]. Automation of Electric Power Systems, 2021, 45(24): 30-40.

[19] Zhou H, Wang H, Jia H, et al. A System Integration Method for Low-carbon Renovation of Electricity-Hydrogen-Gas-Heat PIES[J/OL]. Automation of Electric Power Systems, 2025. https://link.cnki.net/urlid/32.1180.TP.20250306.1627.004.

[20] Wang J, Jia H, Jin X, et al. Low-carbon Operation Optimization Method for Distributed Smart Grid Based on Electricity-Hydrogen-Heat Peer-to-peer Trading[J]. Automation of Electric Power Systems, 2025, 49(9): 40-51.

[21] Lu Y, Yu X, Jin X, et al. Bi-Level Optimization Framework for Buildings to Heating Grid Integration in Integrated Community Energy Systems[J]. IEEE Transactions on Sustainable Energy, 2021, 12(2): 860-873.

[22] Jia H, Wang H, Jin X, et al. Hierarchical and Distributed Optimal Scheduling for Microgrid System Integrating Differentiated Building Clusters [J]. Automation of Electric Power Systems, 2024, 48(22): 96-107.

[23] Du L, Jin X, He W, et al. A Tie-line Power Smoothing Control Method for an Office Building Microgrid by Scheduling Thermal Mass of the Building and Plug-in Electric Vehicles[J]. Electric Power Construction, 2019, 40(8): 26-33.

[24] Ma Q, Jia H, Guo C, et al. Stackelberg Game Optimization Strategy of Virtual Power Plants and Electric Vehicles Based on Conditional Value-at-Risk[J]. Electric Power Construction, 2025, 46(7): 53-66.

[25] Liu W, Xiao H, Zeng L, et al. Optimal Scheduling of Integrated Energy Systems Considering Electric Vehicle Charging Patterns and Supply-Demand Flexibility[J]. Electric Power Construction, 2025, 46(6): 1-12.

[26] Wu Y A, Lau Y yip, Xu J, et al. A hierarchical carbon trading and optimisation scheduling strategy for integrated energy system with electric vehicles[J]. IET Smart Grid, 2025, 8(1): e70001.

[27] Xiao Y, Qian B, Ou J, et al. Optimized scheduling of integrated energy systems considering electric vehicles and carbon emission trading[J]. IEEE Access, 2025, 13: 74147-74162.

[28] Jia H, Xu C, Jin X, et al. Decision-making Methods for Electrolytic Aluminum Enterprises Participating in the Electricity-carbon Market, Considering the Joint Trading of Green Certificates and Carbon Emissions [J/OL]. Power System Technology, 2025.

[29] Geng L, Sun C, Song D, et al. Distributed collaborative optimization of integrated transportation-power energy systems considering dynamic wireless charging[J]. IEEE Access, 2024, 12: 121416-121432.

[30] Geng L, Sun C, Song D, et al. Collaborative optimization framework for coupled power and transportation energy systems incorporating integrated demand responses and electric vehicle battery state-of-charge[J]. Energies, 2024, 17(20).

[31] Zhang J, Wang X, Jiang C, et al. Optimal Scheduling Method of Multi-network Regional Integrated Energy System Based on Traffic Flow Uncertainty[J]. Power System Technology, 2019, 43(9): 3081-3093.

[32] Wang W, Liu J, Lin Z, et al. Resilience assessment of regional electric-thermal integrated energy systems based on diverse user demands[C]// 2024 9th Asia Conference on Power and Electrical Engineering (ACPEE). Shanghai, China: IEEE, 2024: 640-644.

[33] Zhou Z, Zhang X, Guo Q, et al. Integrated pricing framework for optimal power and semi-dynamic traffic flow problem[J]. IET Renewable Power Generation, 2020, 14(18): 3636-3643.

[34] Geng L, Lu Z, He L, et al. Smart charging management system for electric vehicles in coupled transportation and power distribution systems [J]. Energy, 2019, 189: 116275.

[35] Cui Y, Hu Z, Duan X. Optimal pricing of public electric vehicle charging stations considering operations of coupled transportation and power systems[J]. IEEE Transactions on Smart Grid, 2021, 12(4): 3278-3288.