ISSN: 2414-1895 DOI: 10.6919/ICJE.202607_12(7).0012

A Review and Prospect of Optimal Scheduling for Integrated Energy Systems

Ning Guo[1, a], Yingying Zhang[2, b]

[1] School of Economics and Management, Southwest Petroleum University, Chengdu 610500, China

[2] School of Economics and Management, Southwest Petroleum University, Chengdu 610500, China

[a]1980816089@qq.com, [b]17763428734@163.com

Abstract

Optimal scheduling of integrated energy systems (IESs) is a key technical approach for coordinating energy supply and demand, improving multi-energy utilisation efficiency and supporting low-carbon energy transition. To address the fragmented coverage of existing studies, this paper reviews the research progress of IES optimal scheduling from five aspects: theoretical foundations and modelling frameworks, optimisation objectives and constraint systems, core optimisation algorithms, demand response and multi-agent interaction mechanisms, and uncertainty handling methods. The review shows that IES modelling has gradually developed from physical architecture description to energy-hub, microgrid and virtual-power-plant-based aggregation frameworks. Optimisation objectives have evolved from single economic cost minimisation to coordinated economic, environmental and technical performance. Algorithmic research has moved from classical mathematical programming to intelligent optimisation, game-theoretic modelling and data-driven hybrid methods. Integrated demand response and multi-agent coordination have become important sources of operational flexibility, while stochastic optimisation, robust optimisation and distributionally robust optimisation provide complementary tools for handling renewable generation, load, network and market uncertainties. However, current research still faces challenges in dynamic modelling, real-time scheduling, multi-agent benefit coordination, uncertainty modelling efficiency, policy-market coupling and life-cycle optimisation. Future research should further integrate digital twins, blockchain, machine learning and scheduling theory to improve the engineering applicability of IES optimal scheduling.

Keywords

Integrated Energy System; Optimal Scheduling; Energy Hub; Demand Response; Game Theory; Uncertainty Handling.

1. Introduction

The global energy system is undergoing a deep low-carbon transformation. Carbon neutrality strategies and renewable-energy integration have made the coordinated operation of electricity, gas, heat and transport systems increasingly important [1, 2]. In China, the development of the energy internet and integrated energy systems (IESs) has been regarded as a major pathway for improving energy efficiency, promoting multi-energy complementarity and supporting the transition from isolated energy subsystems to coordinated energy service platforms [3, 4]. Compared with conventional single-energy systems, IESs integrate electricity, gas, heat, cooling and other energy

ISSN: 2414-1895 DOI: 10.6919/ICJE.202607_12(7).0012

carriers through coupling devices, storage units and information-control systems, thereby enabling cascade energy utilisation and cross-system flexibility [5].

Optimal scheduling is the operational core of IESs. It determines how generation, conversion, storage, network transfer and demand-side resources should be coordinated under technical, economic and environmental constraints. Mancarella defined multi-energy systems as systems in which different energy vectors interact optimally across spatial scales and service demands [6]. Existing reviews have shown that IES scheduling must address source-network-load-storage interactions, multiple operating objectives and market-oriented decision-making [7]. Multi-microgrid scheduling based on integrated demand response and Stackelberg game also indicates that user-side flexibility and strategic interaction have become essential elements of scheduling models [8].

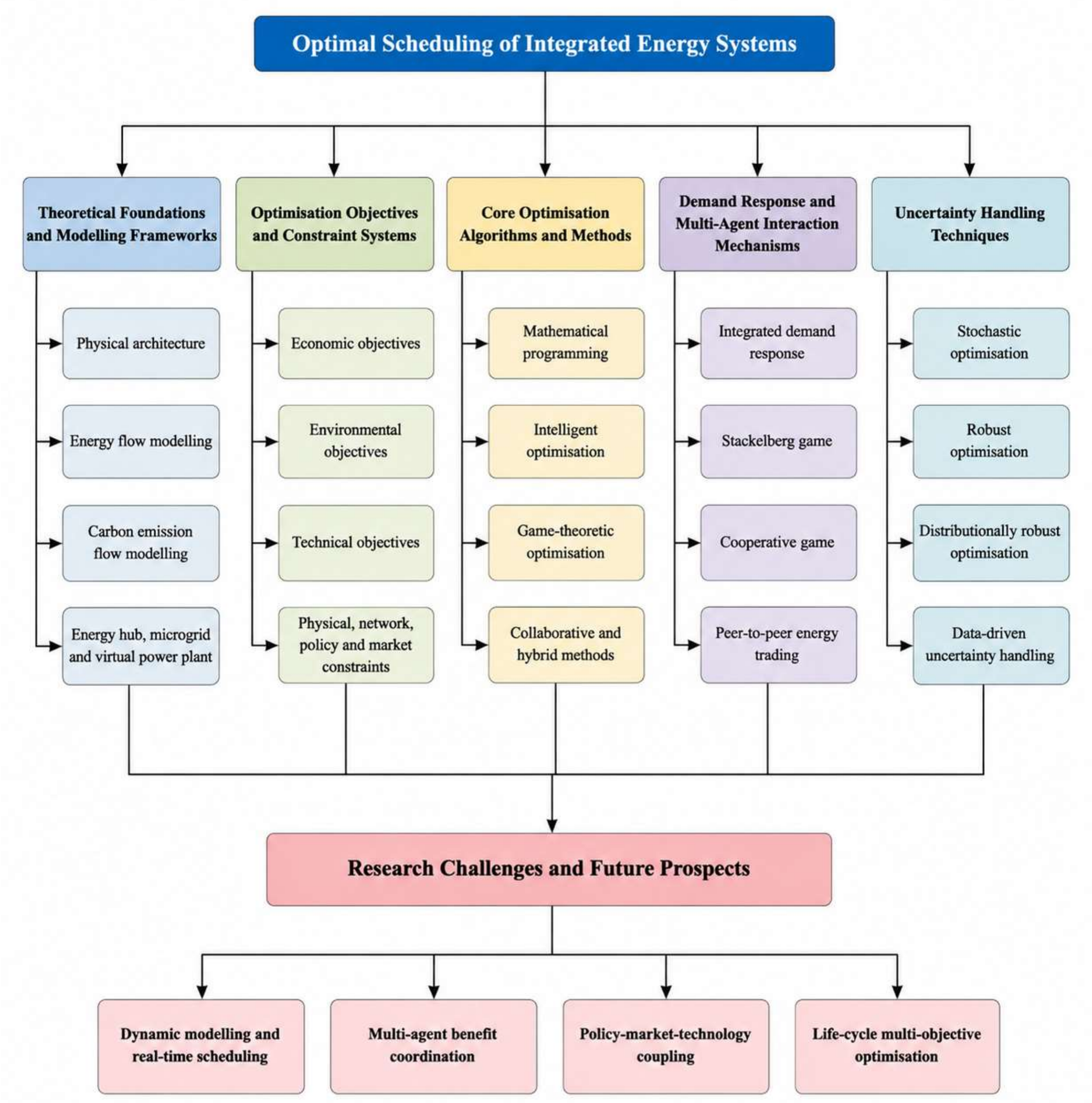

Fig. 1 Review framework of optimal scheduling for integrated energy systems.

Research on IES optimal scheduling has developed along several directions. First, modelling studies have moved from static descriptions of separate energy subsystems to coupled modelling of multi-energy flows, energy conversion devices and aggregated entities [9-11]. Second, physical and network boundaries have been expanded from local energy stations to regional integrated energy systems and electricity-gas coupled systems [12-14]. Third, standardised matrix modelling and multiple-energy-carrier power-flow methods provide a unified mathematical basis for describing energy conversion and transfer [15, 16]. Fourth, hydrogen-related coupling and carbon-flow modelling have strengthened the low-carbon dimension of IES scheduling [17, 18]. Robust low-carbon scheduling with CCUS and user low-carbon preference further demonstrates that carbon reduction is no longer an external evaluation index but an endogenous scheduling objective [19, 20].

Nevertheless, existing research still has limitations. Dynamic characteristics of emerging coupling equipment, such as power-to-hydrogen facilities and hydrogen vehicles, remain insufficiently represented. Multi-agent coordination is often simplified into bilateral games, while real IES operation involves operators, users, aggregators, distribution networks and market entities. Moreover, stochastic optimisation, robust optimisation and distributionally robust optimisation each face trade-offs between accuracy, conservatism and computational efficiency. Therefore, this paper reorganises the research progress of IES optimal scheduling and discusses future directions from a systematic perspective.

Fig. 1 presents the review framework adopted in this paper. The framework is organised around five closely related dimensions of IES optimal scheduling: theoretical foundations and modelling frameworks, optimisation objectives and constraint systems, core optimisation algorithms and methods, demand response and multi-agent interaction mechanisms, and uncertainty handling techniques. These dimensions reflect the main logical chain of IES scheduling research, from system representation and objective formulation to algorithmic solution, flexible resource coordination and uncertainty management. Based on this framework, the paper further identifies the major research challenges and future directions, including dynamic modelling and real-time scheduling, multi-agent benefit coordination, policy-market-technology coupling and life-cycle multi-objective optimisation.

2. Theoretical Foundations and Modelling Frameworks

The modelling of IESs aims to describe multi-energy coupling relationships in a mathematically tractable way. In general, IES modelling includes physical architecture modelling, energy-flow and carbon-emission-flow modelling, and aggregation-based modelling concepts. These modelling methods provide the basic representation for subsequent objective formulation, constraint construction and algorithmic solution.

2.1 Physical Architecture Modelling

From the perspective of physical modelling, IESs generally include energy supply units, conversion equipment, storage devices, energy networks and multi-type loads. Typical coupling equipment includes combined heat and power units, gas boilers, electric boilers, heat pumps, power-to-gas units and hydrogen storage systems. Stochastic design of wind-integrated energy hubs has shown that renewable generation and storage should be co-optimised within the hub structure [24]. Mixed-integer linear programming-based configuration planning further demonstrates that investment and operation can be jointly formulated from the initial system design stage [25]. Techno-economic and environmental modelling of flexible distributed multi-generation options also indicates that the modelling framework should incorporate equipment efficiency, emission factors and operational flexibility [26].

Network modelling is another key component of physical architecture modelling. Electricity networks are constrained by power balance, transmission capacity and voltage-security limits; gas networks are constrained by gas-flow balance and pressure limits; heat networks are influenced by temperature, flow rate and thermal inertia. Reliability assessment is also necessary because component failures, load interruptions and reserve insufficiency directly affect the feasibility of

ISSN: 2414-1895 DOI: 10.6919/ICJE.202607_12(7).0012

scheduling decisions [27]. In electricity-gas coupled regional systems, gas-network states significantly influence power-system operation through gas-fired units, which means that simplified single-network modelling may underestimate operational risk [14].

2.2 Energy Flow and Carbon Emission Flow Modelling

Carbon emission flow modelling has enriched low-carbon IES scheduling. The carbon emission flow method traces the allocation and transfer of carbon emissions through energy flows, allowing scheduling models to identify where emissions are generated and how they are transmitted [18]. When combined with CCUS and multi-energy conversion, carbon-flow modelling can support robust low-carbon scheduling of electricity-gas-heat systems [19]. User low-carbon willingness can also be incorporated into regional IES scheduling, linking environmental preference with demand-side flexibility [20].

2.3 Aggregation-Based Modelling Concepts

Energy hubs are one of the most influential aggregation-based modelling frameworks. They represent the conversion, storage and distribution of different energy carriers through input-output relationships, and have been extensively reviewed as a state-of-the-art modelling tool [21]. Recent work on multi-energy systems with associated energy hubs further confirms that energy hubs provide a unified platform for analysing multi-energy conversion, storage and scheduling [22]. Energy hub networks can also be optimised to improve economic and emission performance, showing their applicability to regional and multi-node IES planning and operation [23].

3. Optimisation Objectives and Constraint Systems

With the development of low-carbon energy systems and energy markets, IES scheduling has evolved from single cost minimisation to a multi-objective optimisation problem involving economic, environmental and technical objectives. At the same time, the constraint system has expanded from basic equipment constraints to physical, network, policy and market constraints.

Cost and emission objectives are often coupled. Energy hub optimisation has demonstrated that economic and emission considerations can be jointly improved through coordinated dispatch of multi-energy resources [23]. Stochastic design of energy hubs further shows that investment cost and operating cost should be evaluated simultaneously when renewable uncertainty is considered [24]. Flexible distributed multi-generation modelling also emphasises the trade-off among economic cost, environmental impact and system flexibility [26].

3.1 Multi-Dimensional Optimisation Objectives

3.1.1 Economic Objectives

Early IES scheduling mainly focused on operating cost minimisation. With the development of low-carbon energy systems and energy markets, the objective system has expanded to include economic, environmental and technical dimensions. Economic objectives usually involve fuel cost, energy purchasing cost, maintenance cost, storage operation cost, demand response compensation and market transaction revenue. Environmental objectives include CO2 emission reduction, pollutant control and carbon-trading cost. Technical objectives include energy efficiency, renewable-energy accommodation, reliability, load fluctuation reduction and equipment operating security.

3.1.2 Environmental Objectives

Environmental objectives include CO2 emission reduction, pollutant control and carbon-trading cost. Cost and emission objectives are often coupled. Energy hub optimisation has demonstrated that economic and emission considerations can be jointly improved through coordinated dispatch of multi-energy resources [23]. Flexible distributed multi-generation modelling also emphasises the trade-off among economic cost, environmental impact and system flexibility [26].

Volume 12 Issue 7, 2026
DOI: 10.6919/ICJE.202607_12(7).0012

3.1.3 Technical Objectives

Technical objectives include energy efficiency, renewable-energy accommodation, reliability, load fluctuation reduction and equipment operating security. In practical scheduling, technical objectives are usually coupled with economic and environmental objectives because operating security, renewable accommodation and equipment performance directly influence both system cost and carbon emissions.

3.2 Multiple Types of Constraints

3.2.1 Physical Constraints

Physical constraints include equipment capacity limits, ramping limits, energy conversion efficiency, storage state-of-charge limits, charge-discharge efficiency and minimum or maximum operating output. These constraints ensure that scheduling decisions remain feasible within the operating boundaries of generation, conversion and storage equipment.

3.2.2 Network Constraints

Network constraints include electricity transmission limits, gas pipeline constraints, heat network balance and coupling relationships among different networks. These constraints are essential for describing the physical transfer of electricity, gas and heat, especially in regional IESs where multi-network coupling significantly affects scheduling feasibility.

3.2.3 Policy and Market Constraints

Market and policy constraints involve energy prices, carbon emission allowances, subsidies, demand response incentives and transaction rules. Game-based scheduling of park-level IESs considering demand response incentives shows that price signals and incentive mechanisms can significantly influence both operator decisions and user responses [28]. Cooperative-game-based coordination between microgrids and distribution networks also indicates that transaction prices and benefit allocation rules should be embedded into the scheduling model [29].

Demand response constraints are especially important in integrated energy systems. Residential energy-hub studies have shown that combining demand response and energy storage can reduce energy cost and improve operational flexibility [30]. In regional systems, demand response can be extended from electricity loads to heat and cooling loads, thereby exploiting the thermal inertia of buildings and the shiftability of multi-energy demand. These constraints make the model more realistic but also increase its nonlinearity and computational complexity.

4. Core Optimisation Algorithms and Methods

IES scheduling problems are usually large-scale, nonlinear, multi-objective and uncertainty-sensitive. Therefore, different types of optimisation methods have been developed, including traditional mathematical programming, intelligent optimisation, game-theoretic optimisation and collaborative hybrid methods.

4.1 Traditional Optimisation Algorithms

Classical mathematical programming remains the foundation of IES scheduling. Linear programming, nonlinear programming, mixed-integer linear programming and mixed-integer nonlinear programming are widely used to formulate unit commitment, energy conversion, storage operation and network constraints. MILP is particularly common because it can represent discrete equipment states while maintaining relatively strong solvability. However, linearisation may reduce modelling accuracy, and large-scale systems with multiple networks and uncertainty sources may lead to high computational burden.

Robust optimisation is widely applied when accurate probability distributions are unavailable. Two-stage robust scheduling of regional IESs considering network constraints and source-load uncertainty improves system feasibility under adverse scenarios [31]. Robust stochastic scheduling with refined power-to-gas modelling further enhances the representation of multi-energy conversion under

ISSN: 2414-1895
DOI: 10.6919/ICJE.202607_12(7).0012

uncertainty [32]. Distributionally robust coordinated scheduling of integrated electricity-gas systems considers higher-order wind uncertainty and avoids excessive dependence on exact probability distributions [33]. Day-ahead economic dispatch based on distributionally robust optimisation also demonstrates the potential of this method in electricity-gas-heat systems [34]. The theoretical basis of robust optimisation is closely related to the trade-off between robustness and economy, as discussed in the price of robustness framework [35]. Wasserstein-metric-based data-driven stochastic optimisation provides another way to construct ambiguity sets from limited data [36].

Stochastic optimisation is suitable when historical data and probability distributions are available. Planning and scheduling of energy hubs under wind, storage and demand response uncertainty shows that scenario generation and reduction can represent renewable and load uncertainty in a tractable way [37]. However, stochastic optimisation requires a sufficient number of scenarios and its performance depends on distribution accuracy. Therefore, hybrid methods combining stochastic optimisation, robust optimisation and distributionally robust optimisation are increasingly used.

4.2 Intelligent Optimisation Algorithms

Intelligent optimisation algorithms provide another solution path for nonlinear, nonconvex and multi-objective scheduling problems. Multi-agent genetic algorithms can handle economic dispatch of energy hubs constrained by wind availability and reflect decentralised decision-making [38]. Model predictive control has been applied to microgrid operation optimisation, showing advantages in rolling scheduling and real-time correction [39]. Robust optimisation approaches to energy hub management provide additional support for scheduling under uncertain operating conditions [40]. Distributionally robust decentralised scheduling between transmission markets and local energy hubs further suggests that decentralised coordination is becoming an important direction for large-scale IESs [41].

4.3 Game Theory and Collaborative Optimisation Algorithms

Game theory and collaborative optimisation are mainly used to describe the interaction among multiple stakeholders in IES scheduling. Stackelberg games are suitable for leader-follower relationships, while cooperative games are used to model alliance formation and benefit allocation. Collaborative optimisation methods can decompose large-scale scheduling problems into several subproblems and coordinate the solutions among different agents, thereby improving computational efficiency and supporting decentralised decision-making.

5. Demand Response and Multi-Agent Interaction Mechanisms

Demand response and multi-agent interaction are important mechanisms for improving IES flexibility. They enable demand-side resources and market participants to participate in scheduling decisions through price signals, incentives, energy trading and benefit allocation.

5.1 Integrated Demand Response Modelling

Demand response is a major flexibility source in IES scheduling. It allows users to adjust electricity, heat, cooling and transport-related loads according to price signals, incentives or system requirements. Stochastic scheduling of plug-in electric vehicle aggregators shows that electric vehicles can participate in energy and ancillary service markets and provide temporal flexibility [42]. Integrated demand-side management games in smart energy hubs further demonstrate that user decisions can be coordinated through game-theoretic mechanisms [43].

5.2 Multi-Agent Game-Based Coordination Mechanisms

Multi-agent interaction is increasingly important because IESs involve operators, aggregators, users, distributed generators, storage owners and market platforms. Stackelberg game is suitable for leader-follower structures, in which an operator or service provider sets prices and users respond by adjusting demand. Energy-sharing for photovoltaic prosumer clusters based on stochastic programming and Stackelberg game provides a representative example of combining uncertainty modelling with

ISSN: 2414-1895 DOI: 10.6919/ICJE.202607_12(7).0012

strategic interaction [44]. Peer-to-peer energy trading in microgrids shows that decentralised transactions can improve local energy utilisation and user autonomy [45].

Cooperative games are used when multiple entities form alliances to improve total benefits. Benefit allocation is the central issue, and methods such as Shapley value, bargaining models and improved allocation rules are commonly adopted. In IES scheduling, cooperative mechanisms can reduce total cost, improve renewable-energy accommodation and enhance fairness among participants. However, many existing models assume complete information and stable user behaviour. In real markets, information asymmetry, bounded rationality and dynamic prices may weaken the effectiveness of static game models. Blockchain-based transaction records and smart contracts may improve transparency, but their integration with scheduling models still requires further study.

6. Uncertainty Handling Techniques

Uncertainty is one of the core issues in IES optimal scheduling. Renewable generation, multi-energy loads, equipment states, network conditions and market prices all introduce uncertainty into scheduling decisions. Therefore, uncertainty modelling and handling methods are essential for improving the reliability and economy of IES operation.

6.1 Sources and Characterisation of Uncertainty

IES scheduling is affected by uncertainties from renewable generation, multi-energy loads, equipment states, network conditions and market prices. Wind and photovoltaic output are intermittent and weather-dependent. Electricity, gas, heat and cooling loads fluctuate with user behaviour and temperature. Network failures and equipment ageing affect reliability. Energy prices and carbon prices introduce market risk. Therefore, uncertainty handling is essential for practical scheduling.

6.2 Applications of Uncertainty Handling Algorithms

Stochastic optimisation describes uncertainty through probability distributions and scenarios. It can provide economically efficient decisions when probability information is reliable, but it may suffer from scenario explosion. Robust optimisation uses uncertainty sets and focuses on feasibility under worst-case conditions, but its solutions may be conservative. Distributionally robust optimisation balances these two methods by considering a family of probability distributions around empirical data. In addition, integrated electrical and gas network flexibility assessment in low-carbon multi-energy systems indicates that flexibility should be evaluated across coupled networks rather than within a single energy carrier [46].

Uncertainty handling is moving towards data-driven and hybrid approaches. Machine learning can be used for renewable output forecasting, load prediction and scenario generation, while optimisation algorithms determine feasible and economical schedules. Future models should better coordinate data prediction, uncertainty-set construction, real-time scheduling and risk evaluation. This is particularly important for systems with high renewable penetration, hydrogen storage, electric vehicles and flexible loads.

7. Research Challenges and Future Prospects

Although IES optimal scheduling has made significant progress, several challenges still restrict its theoretical development and engineering application. Future studies should focus on dynamic modelling, real-time computation, multi-agent coordination, uncertainty handling, policy-market coupling and life-cycle optimisation.

7.1 Current Research Challenges

Current IES scheduling research still faces several challenges. First, dynamic modelling is insufficient. Many models are based on static energy balance and simplified conversion efficiency, while the transient behaviour of power-to-hydrogen units, thermal storage, heat networks and hydrogen vehicles is not fully described. Second, real-time scheduling remains difficult. The integration of

ISSN: 2414-1895 DOI: 10.6919/ICJE.202607_12(7).0012

multiple networks, integer variables and uncertainty sets increases computational burden, which limits engineering application. Third, multi-agent coordination is still simplified. Existing studies often focus on bilateral games, while real IES markets require coordination among multiple operators, aggregators, users and network entities. Fourth, uncertainty handling still involves a trade-off between accuracy and efficiency. Stochastic optimisation may be computationally expensive, robust optimisation may be conservative, and distributionally robust optimisation still depends on suitable ambiguity-set construction. Fifth, policy and market mechanisms are not fully coupled with scheduling models. Carbon trading, subsidies, multi-energy prices and user low-carbon preferences should be jointly considered. Finally, life-cycle optimisation is still limited. Equipment ageing, replacement, retirement cost and environmental impacts across planning, operation and decommissioning stages need more attention.

7.2 Future Research Directions

Future research can be developed in five directions. First, dynamic collaborative scheduling should be combined with digital twin technology. Real-time mapping between physical systems and virtual models can support online simulation, fault recovery and adaptive scheduling. Second, multi-agent hybrid game models should be developed to describe both competition and cooperation among distribution networks, microgrids, aggregators and users. Blockchain can be introduced to improve transaction transparency and benefit allocation traceability. Third, data-driven uncertainty handling should be strengthened by integrating machine learning, stochastic optimisation, robust optimisation and distributionally robust optimisation. Fourth, policy-market-technology coordinated scheduling should be improved by incorporating carbon trading, multi-energy market prices, subsidies and user participation behaviour. Fifth, life-cycle multi-objective optimisation should be developed to integrate planning, operation and retirement decisions, thereby reducing total cost and environmental impact over the full system life cycle.

8. Conclusion

This paper reviews the research progress of optimal scheduling for integrated energy systems from the perspectives of modelling frameworks, optimisation objectives and constraints, optimisation algorithms, demand response and multi-agent interaction, and uncertainty handling. The results show that IES scheduling has developed from single-objective and single-energy dispatch to multi-energy, multi-objective, multi-agent and uncertainty-aware optimisation. Energy hubs, microgrids and virtual power plants provide important modelling tools; economic, environmental and technical objectives form a coordinated optimisation framework; mathematical programming, intelligent optimisation and game theory provide complementary solution methods; and stochastic, robust and distributionally robust optimisation support scheduling under uncertainty.

Despite these advances, IES optimal scheduling still requires further improvement in dynamic modelling, real-time computation, multi-agent benefit coordination, uncertainty handling, policy-market coupling and life-cycle optimisation. The integration of digital twins, blockchain, machine learning and advanced optimisation theory is expected to enhance the adaptability, transparency and engineering practicality of future IES scheduling. These developments will provide theoretical and technical support for clean, low-carbon, secure and efficient modern energy systems.

Acknowledgments

The authors would like to thank Southwest Petroleum University for its academic support.

References

[1] Zhang, X. L., Huang, X. D., Zhang, D., et al. (2022). Energy-economic transition pathway and policy under carbon neutrality target. *Management World*, *38*(1), 35–66. (In Chinese)

[2] Ma, S. C., & Fan, Y. (2022). Challenges and opportunities in low-carbon energy system transition: Vehicle-grid integration for renewable energy accommodation. *Management World*, *38*(5), 209–223, 239. (In Chinese)

[3] Sun, H. B., Guo, Q. L., Pan, Z. G., et al. (2015). Energy internet: Driving force, review and outlook. *Power System Technology*, *39*(11), 3005–3013. (In Chinese)

[4] Sun, H. B., Guo, Q. L., & Pan, Z. G. (2015). Energy internet: Concept, architecture and frontier outlook. *Automation of Electric Power Systems*, *39*(19), 1–8. (In Chinese)

[5] Zeng, M., Liu, Y. X., Zhou, P. C., et al. (2018). Review and prospect of integrated energy system modelling and benefit evaluation. *Power System Technology*, *42*(6), 1697–1708. (In Chinese)

[6] Mancarella, P. (2014). MES (multi-energy systems): An overview of concepts and evaluation models. *Energy*, *65*, 1–17.

[7] Li, J. H., Zhu, M. S., Lu, Y. J., et al. (2021). Review of optimal scheduling of integrated energy systems. *Power System Technology*, *45*(6), 2256–2272. (In Chinese)

[8] Li, P., Wu, D. F., Li, Y. W., et al. (2021). Optimal scheduling strategy of multi-microgrid integrated energy system based on integrated demand response and Stackelberg game. *Proceedings of the CSEE*, *41*(4), 1307–1321, 1538. (In Chinese)

[9] Ai, Q., & Hao, R. (2018). Key technologies and challenges of multi-energy complementarity and integrated optimisation energy systems. *Automation of Electric Power Systems*, *42*(4), 2–10, 46. (In Chinese)

[10] Cheng, H. Z., Hu, X., Wang, L., et al. (2019). Review of regional integrated energy system planning. *Automation of Electric Power Systems*, *43*(7), 2–13. (In Chinese)

[11] Zhang, S. H., Gu, W., Yu, R. Z., et al. (2024). Modelling and simulation of integrated energy systems: Review, reflection and prospect. *Automation of Electric Power Systems*, *48*(17), 1–21. (In Chinese)

[12] Jia, H. J., Wang, D., Xu, X. D., et al. (2015). Research on some key problems related to regional integrated energy systems. *Automation of Electric Power Systems*, *39*(7), 198–207. (In Chinese)

[13] Wang, W. L., Wang, D., Jia, H. J., et al. (2016). Review of steady-state analysis of typical regional integrated energy systems under the background of energy internet. *Proceedings of the CSEE*, *36*(12), 3292–3306. (In Chinese)

[14] Wang, W. L., Wang, D., Jia, H. J., et al. (2017). Steady-state analysis of electricity-natural gas regional integrated energy systems considering natural gas network states. *Proceedings of the CSEE*, *37*(5), 1293–1305. (In Chinese)

[15] Geidl, M., & Andersson, G. (2005). A modeling and optimization approach for multiple energy carrier power flow. In *2005 IEEE Russia Power Tech* (pp. 1–7). IEEE.

[16] Wang, Y., Zhang, N., Kang, C., et al. (2017). Standardized matrix modeling of multiple energy systems. *IEEE Transactions on Smart Grid*, *10*(1), 257–270.

[17] Zhu, Z. S., Guo, L., & Luo, G. H. (2025). Event-triggered distributionally robust optimal scheduling of electricity-gas-hydrogen integrated energy systems considering hydrogen vehicle demand response. *Power System Technology*, *49*(8), 3219–3229. (In Chinese)

[18] Zhou, T. R., Kang, C. Q., Xu, Q. Y., et al. (2012). Preliminary investigation on calculation methods of carbon emission flow in power systems. *Automation of Electric Power Systems*, *36*(11), 44–49. (In Chinese)

[19] Luo, P., Yan, W. L., Wang, Y., et al. (2022). Robust optimal scheduling of electricity-gas-heat integrated energy systems considering CCUS. *High Voltage Engineering*, *48*(6), 2077–2087. (In Chinese)

[20] Xiong, Z., Wang, S., Wang, L. L., et al. (2024). Robust optimal scheduling of regional integrated energy systems considering multi-energy complementary flexibility and user low-carbon willingness. *Power System Technology*, *48*(7), 2691–2701. (In Chinese)

[21] Sadeghi, H., Rashidinejad, M., Moeini-Aghtaie, M., et al. (2019). The energy hub: An extensive survey on the state-of-the-art. *Applied Thermal Engineering*, *161*, 114071.

[22] Son, Y. G., Oh, B. C., Acquah, M. A., et al. (2021). Multi energy system with an associated energy hub: A review. *IEEE Access*, *9*, 127753–127766.

[23] Maroufmashat, A., Elkamel, A., Fowler, M., et al. (2015). Modeling and optimization of a network of energy hubs to improve economic and emission considerations. *Energy*, *93*, 2546–2558.

[24] Dolatabadi, A., Mohammadi-Ivatloo, B., Abapour, M., et al. (2017). Optimal stochastic design of wind integrated energy hub. *IEEE Transactions on Industrial Informatics*, *13*(5), 2379–2388.

[25] Wang, Y., Zhang, N., Zhuo, Z., et al. (2018). Mixed-integer linear programming-based optimal configuration planning for energy hub: Starting from scratch. *Applied Energy*, *210*, 1141–1150.

[26] Capuder, T., & Mancarella, P. (2014). Techno-economic and environmental modelling and optimization of flexible distributed multi-generation options. *Energy*, *71*, 516–533.

[27] Li, G. F., Huang, Y. X., Bie, C. H., et al. (2019). Review and prospect of operation reliability assessment for integrated energy systems. *Electric Power Automation Equipment*, *39*(8), 12–21. (In Chinese)

[28] Wang, L. Y., Lin, J. L., Song, M. Q., et al. (2023). Game-based optimal scheduling of park-level integrated energy systems considering demand response incentive mechanisms. *Control and Decision*, *38*(11), 3192–3200. (In Chinese)

[29] Fan, T. Y., Wang, H. Y., Wang, W. Q., et al. (2022). Coordinated optimal scheduling of microgrid-distribution network based on cooperative game considering active and passive demand response. *Power System Technology*, *46*(2), 453–463. (In Chinese)

[30] Brahman, F., Honarmand, M., & Jadid, S. (2015). Optimal electrical and thermal energy management of a residential energy hub, integrating demand response and energy storage system. *Energy and Buildings*, *90*, 65–75.

[31] Guo, Z., Li, G. Y., Zhou, M., et al. (2019). Two-stage robust optimal scheduling of regional integrated energy systems considering network constraints and source-load uncertainty. *Power System Technology*, *43*(9), 3090–3100. (In Chinese)

[32] Zhu, L., Wang, J., Tang, L. J., et al. (2019). Robust stochastic optimal scheduling of integrated energy systems considering refined power-to-gas modelling. *Power System Technology*, *43*(1), 116–126. (In Chinese)

[33] Zhang, Y. C., Zheng, F., Le, J., et al. (2020). Distributionally robust coordinated optimal scheduling of integrated electricity-gas systems considering high-order wind power uncertainty. *Proceedings of the CSEE*, *40*(24), 8012–8026, 8238. (In Chinese)

[34] Gao, X. S., Li, G. F., Xiao, Y., et al. (2020). Day-ahead economic dispatch of electricity-gas-heat integrated energy systems based on distributionally robust optimisation. *Power System Technology*, *44*(6), 2245–2254. (In Chinese)

[35] Bertsimas, D., & Sim, M. (2004). The price of robustness. *Operations Research*, *52*(1), 35–53.

[36] Zhao, C., & Guan, Y. (2018). Data-driven risk-averse stochastic optimization with Wasserstein metric. *Operations Research Letters*, *46*(2), 262–267.

[37] Pazouki, S., & Haghifam, M. R. (2016). Optimal planning and scheduling of energy hub in presence of wind, storage and demand response under uncertainty. *International Journal of Electrical Power & Energy Systems*, *80*, 219–239.

[38] Moeini-Aghtaie, M., Dehghanian, P., Fotuhi-Firuzabad, M., et al. (2013). Multiagent genetic algorithm: An online probabilistic view on economic dispatch of energy hubs constrained by wind availability. *IEEE Transactions on Sustainable Energy*, *5*(2), 699–708.

[39] Parisio, A., Rikos, E., & Glielmo, L. (2014). A model predictive control approach to microgrid operation optimization. *IEEE Transactions on Control Systems Technology*, *22*(5), 1813–1827.

[40] Parisio, A., Del Vecchio, C., & Vaccaro, A. (2012). A robust optimization approach to energy hub management. *International Journal of Electrical Power & Energy Systems*, *42*(1), 98–104.

[41] Yin, S., & Wang, J. (2022). Distributionally robust decentralized scheduling between the transmission market and local energy hubs. *IEEE Transactions on Power Systems*, *38*(2), 1845–1856.

[42] Alipour, M., Mohammadi-Ivatloo, B., Moradi-Dalvand, M., et al. (2017). Stochastic scheduling of aggregators of plug-in electric vehicles for participation in energy and ancillary service markets. *Energy*, *118*, 1168–1179.

[43] Sheikhi, A., Rayati, M., Bahrami, S., et al. (2015). Integrated demand side management game in smart energy hubs. *IEEE Transactions on Smart Grid*, *6*(2), 675–683.

[44] Liu, N., Cheng, M., Yu, X., et al. (2018). Energy-sharing provider for PV prosumer clusters: A hybrid approach using stochastic programming and Stackelberg game. *IEEE Transactions on Industrial Electronics*, *65*(8), 6740–6750.

[45] Zhang, C., Wu, J., Zhou, Y., et al. (2018). Peer-to-peer energy trading in a microgrid. *Applied Energy*, *220*, 1–12.

[46] Clegg, S., & Mancarella, P. (2015). Integrated electrical and gas network flexibility assessment in low-carbon multi-energy systems. *IEEE Transactions on Sustainable Energy*, *7*(2), 718–727.