A Review of Optimal Scheduling and Distributed Cooperative Control for Smart Grids Integrated with Electric Vehicles

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***Abstract*—The technological development of smart grids (SGs) has recently gained increased momentum due to large-scale integration of renewable energy sources (e. g., wind and photovoltaic power) and highly variable loads, including electric vehicles (EVs) along with the deepened decarbonization in power and transport systems as two major greenhouse gas-emitting sectors worldwide. With the development of SGs, fruitful achievements in optimal scheduling and distributed cooperative control have been made. However, a comprehensive survey of these methods covering the low-carbon, economy, and cybersecurity metrics is still missing. This paper bridges the gap with the aim of providing an in-depth overview of optimal scheduling and distributed cooperative control from the whole system perspective within the SG framework. First, the fundamental mathematical models of optimal scheduling for low-carbon, economy, and cybersecurity operations are reviewed, the corresponding solution methods are summarized, and the cooperative optimization and scheduling methods for SGs integrated with EVs are specifically analyzed. Second, the performances of centralized and distributed cooperative control methods are compared, and two popular distributed cooperative control frameworks, namely centralized-distributed and autonomous-distribute frameworks, are further discussed comprehensively. Third, typical real-world applications of optimal scheduling and distributed cooperative control are analyzed. Finally, the trends and challenges of optimal scheduling and distributed cooperative control for effectively integrating EVs in SGs are prospected.**

***Index Terms*—Smart grid (SG), electric vehicle (EV), low-carbon, economy, and cybersecurity operations, optimal scheduling, distributed cooperative control.**

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Nomenclature

A. Sets

J	Number of targets
K, L, Q	Numbers of objectives, equality constraints, and inequality constraints
M	Number of thermal units
N	Number of elements
N_{bus}	Number of buses
T	Number of time periods

B. Parameters and Variables

$\alpha_m, \beta_m, \gamma_m$	Carbon emission coefficients of thermal unit m
π_b, π_s	Prices of emission allowances bought and sold on carbon emission trading (CET)
θ_i, θ_j	Voltage phase angles of buses i and j
θ_{ij}	Voltage phase angle difference between buses i and j
a_m, b_m, c_m	Cost coefficients of thermal unit m
C_{CET}	CET cost
$C_m(\cdot)$	Operating cost of thermal unit m
d_n	Defense resource amount allocated to element n, with $\boldsymbol{d}=[d_1, d_2, \ldots, d_N]$ denoting the defense resource allocation vector
d_{prevent}	Budget for protecting components
E_0	Carbon quota
E_b, E_s	Amounts of emission allowances bought from and sold to CET
$E_b^{\max}, E_s^{\max}$	The maximum emission allowances bought from and sold to CET
$E_m(\cdot)$	Carbon emission of thermal unit m
$f_k(\boldsymbol{x})$	The k^{th} objective function

G_{ij}, B_{ij}	Conductance and susceptance of the $(i,j)^{\text{th}}$ element in bus admittance matrix
$g_q(\boldsymbol{x}), h_l(\boldsymbol{x})$	The q^{th} inequality constraint and the l^{th} equality constraint
P_i^D, P_i^G	Active power demand and generation at bus i
$P_{i,j}^{\max}$	The maximum active power flow of line (i,j)
$P_{L,t}$	Load at time t
P_{loss}	Transmission loss
$P_m^{\max}, P_m^{\min}$	Upper and lower limits of power output for thermal unit m
$P_{m,t}^{TG}$	Active power output of thermal unit m at time t
$P(Y_j > y_{\min})$	Probability that attack outcome exceeds threshold
p_n	Protection level of element n
$\mathcal{P}_n(\cdot)$	Protection function of element n
q_j	Probability that target j is attacked, with $\boldsymbol{q} = [q_1, q_2, \ldots, q_J]$ denoting the attack probability vector
RD_m, RU_m	Ramping down and up limits of thermal unit m
$SD_{m,t}^{TG}, SU_{m,t}^{TG}$	Shut-down and start-up costs of thermal unit m at time t
SR_t, OR_t	System spinning and operating reserve requirements at time t
$SR_{m,t}^{TG}, OR_{m,t}^{TG}$	Spinning and operating reserves provided by thermal unit m at time t
$u_j(\cdot)$	Loss caused by attacking target
$U_{m,t}^{TG}$	On/off status of thermal unit m at time t
V_i, V_j	Voltage magnitudes of buses i and j
$V_{i,t}$	Voltage magnitude of bus i at time t
$V_i^{\min}, V_i^{\max}$	The minimum and maximum voltage magnitudes of bus i
$\boldsymbol{x}$	Decision vector
$X_{i,j}$	Reactance of line (i,j)
Y_j	Outcome of attacking target j
$y_{\min}$	Threshold magnitude for attack outcome

I. Introduction

THE fast-growing power demand worldwide due to industrialization and urbanization has heightened the global climate and environmental challenges due to substantive consumption of fossil fuels in the electricity and transportation sectors [1]. The power generation sector alone accounted for 38.6% of the total global carbon emissions in 2024, reaching 14.6 Gt [2], [3]. To reduce carbon emissions, the United Nations has issued related policies (e. g., the Paris Agreement [4]) that encourage the utilization of renewable energy sources (RESs) to gradually replace fossil fuels [5]. For example, the total global addition of renewable energy capacity was 585 GW in 2024, including approximately 452 GW of photovoltaic (PV) capacity and 113 GW of wind power [6]. Moreover, to reduce carbon emissions from transportation, the largest greenhouse gas-emitting sector, new electric-powered transportation technologies such as high-speed trains, subways, and electric vehicles (EVs), are becoming widely adopted worldwide to replace fossil-fuel vehicles. Specifically, with rapid technological advancements and cost reductions, global EV sales reached 4.1 million units in the first quarter of 2025, representing a 29% year-over-year increase in comparison with the same period in 2024 [7]. To support the efficient operation of power grid with significant penetration of RESs and EVs, over 195 million smart meters and communication devices were deployed in the EU27+3 (i. e., the European Union's 27 member states (EU27) plus Norway, Iceland, and Switzerland) by the end of 2024 [8]. Meanwhile, China installed approximately 650 million smart meters in 2024 [9], enhancing system state observability and control responsiveness. These trends have drawn substantive interest from both academic and industry communities.

Driven by the widespread use of RESs, the increasing number of flexible clients, and the development of measurement technologies, conventional power systems have been transformed into smart grids (SGs), promoted by the integration of sensors, measurement devices, smart automation systems, industrial control systems, and communication devices [10], [11]. An architecture of SGs integrated with EVs is shown in Fig. 1, where SGs encompass all domains of the power system including generation, transmission, distribution, and consumption. Specifically, wind power and PV power-dominated RESs are integrated into the generation side, while electric-powered transportation tools such as EVs are incorporated into the consumption side. Moreover, SGs are cyber-based systems that integrate and synchronize underlying physical power system elements. These systems have embedded control systems operating in distributed networks to monitor and control physical power system in real time [12]. In Fig. 1, ES is short for energy storage; and DT is short for distribution transformer.

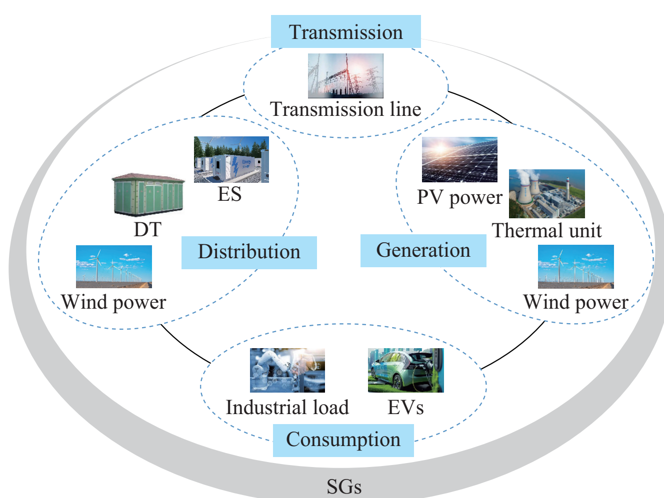

Fig. 1. Architecture of SGs integrated with EVs.

As a growing number of RESs, EVs, smart meters, and intelligent devices with communication functions are connected to SGs, they create a complex system with the tightly coupled power grid and communication networks. Some new challenges are introduced into the optimal scheduling and distributed cooperative control of the whole system, which can be roughly classified into three categories. First, the inherent randomness and volatility of RESs result in uncertain and time-varying power outputs [13], which makes the current optimal scheduling and distributed cooperative control methods hardly adaptable to these new features if the conventional economy metrics are used to formulate the problem. Thus, to maximize the utilization of RESs, the optimal scheduling and distributed cooperative control methods need to be redesigned by adding the low-carbon metrics. Second, when a large number of EVs are integrated into power grid, it leads to a rapid and dramatic load increase, and non-cooperative charging of EVs may compromise reliability of power grid services [14]. Thus, to encourage EVs to provide the flexibility services to the power grid, the current optimal scheduling needs to consider the economy metrics, enabling and incentivizing a more flexible EV charging in an organized manner to realize peak shaving and valley filling [15]. Third, smart meters and intelligent devices with communication functions are commonly weakly-protected or unprotected [16]. If cyber-attacks bypass the naive attack detector, the authenticity and integrity of data may be violated, making the current optimal scheduling and distributed cooperative control methods fail to deliver the expected system performance, or even causing the collapse of power grid [17]. Thus, to guarantee system security, the optimal scheduling and distributed cooperative control methods need to consider the cybersecurity metrics [18], [19].

To address these challenging issues, the state-of-the-art optimal scheduling and distributed cooperative control of SGs are reviewed and summarized in Table I. Based on the low-carbon, economy, and cybersecurity metrics, it is evident from Table I that the existing review papers [20]-[31] primarily focus on either optimal scheduling or distributed cooperative control separately. However, these two aspects are all crucial for the SGs, and their seamless and synergistic integration is important to guarantee low-carbon, economy, and security operations of power grid without compromising cybersecurity. The decision results of optimal scheduling directly affect the execution and parameter adjustment of distributed cooperative control. Furthermore, the execution results of distributed cooperative control also reciprocally influence the formulation of the scheduling problem. Therefore, it is necessary to consider both optimal scheduling and distributed cooperative control simultaneously in one framework [32]-[34]. On the other hand, the low-carbon, economy, and cybersecurity metrics used in optimal scheduling and distributed cooperative control remain to be comprehensively reviewed.

TABLE I
REVIEW OF PUBLISHED LITERATURE RELATED TO OPTIMAL SCHEDULING AND DISTRIBUTED COOPERATIVE CONTROL

Topic	Reference	Content
Optimal scheduling	[20]	Multi-objective optimization scheduling in emissions and cost reductions
	[21]	Economic scheduling models and other ancillary services for multi-area power systems
	[22]	Optimal scheduling problem of security-constrained unit commitment
	[23]	Power optimal scheduling from economic and environmental perspectives
	[24]	Meta-heuristic techniques in microgrids with only economy metrics
	[25]	Charging and discharging management of EVs integrated into SGs
	[26]	Optimal vehicle-to-grid (V2G) scheduling after EV integration
Distributed cooperative control	[27]	Distributed cooperative control methods in microgrids with only cybersecurity metrics
	[28]	Distributed cooperative control for multiagent systems with only economy metrics
	[29]	Distributed cooperative control of theoretical frameworks and applications with only economy metrics
	[30]	Distributed cooperative control for microgrids with only economy metrics
	[31]	Distributed security control in microgrids with only cybersecurity metrics
Optimal scheduling and distributed cooperative control	[32]	Distributed optimal control algorithms with only economy metrics
	[33]	Optimal scheduling and distributed cooperative control without low-carbon metrics
	[34]	Optimal scheduling and distributed cooperative control without cybersecurity metrics

Different from the existing review papers, this paper focuses on both optimal scheduling and distributed cooperative control of SGs, while considering various low-carbon, economy, and cybersecurity metrics. The overall framework of SGs on optimal scheduling and distributed cooperative control is illustrated in Fig. 2, where the models and solution methods of optimal scheduling at the upper level are first reviewed by using low-carbon, economy, and cybersecurity metrics. Subsequently, different distributed cooperative control methods at the lower level are surveyed. Here, the economy metrics are mainly influenced by the generation side, and the low-carbon metrics are influenced by both the generation side and the consumption side such as EVs while the cybersecurity metrics are influenced by intelligent devices with communication functions. In Fig. 2, IED is short for intelligent electronic device; PLC is short for programmable logic controller; PMU is short for phasor measurement unit; and RTU is short for remote terminal unit.

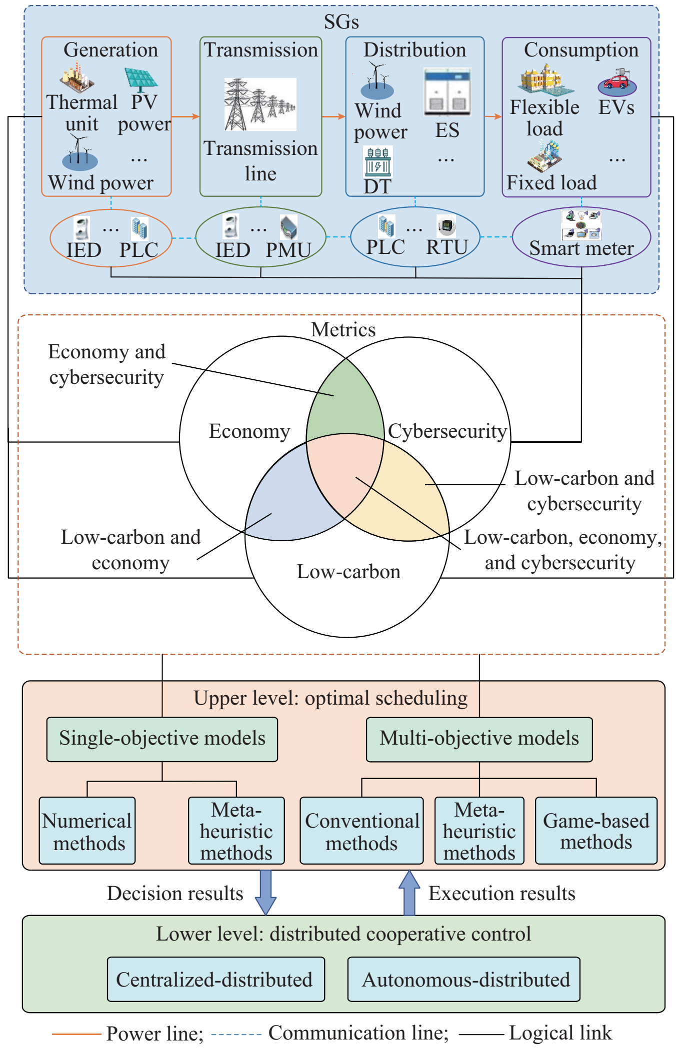

Fig. 2. Research framework of SGs on optimal scheduling and distributed cooperative control.

The rest of this paper is organized as follows. In Section II, the optimal scheduling of SGs considering EVs is reviewed and analyzed from the perspectives of single-objective optimization, multi-objective optimization, and cooperative optimization and scheduling. In Section III, popular frameworks for distributed cooperative control of SGs considering EVs, including centralized-distributed and autonomous-distributed cooperative control, are surveyed. Section IV presents a comprehensive review and analysis of typical applications of optimal scheduling and distributed cooperative control in SGs with EVs. Finally, future research perspectives on optimal scheduling and distributed cooperative control for SGs integrating EVs are discussed in Section V.

II. Optimal Scheduling of SGs Integrated with EVs

Unlike traditional power system scheduling, the optimal scheduling of SGs necessitates a holistic consideration of low-carbon, economy, and cybersecurity metrics. In this section, we first analyze optimal scheduling models of SGs from two different perspectives, i. e., single-objective and multi-objective optimization formulations, and subsequently discuss their corresponding solution methods. Furthermore, the cooperative optimization and scheduling of SGs integrating EVs is examined.

A. Single-objective Optimization

As illustrated in Fig. 3, research on the scheduling of SGs based on single-objective optimization formulation can be divided into two groups, i.e., the models and solution methods for single-objective optimization.

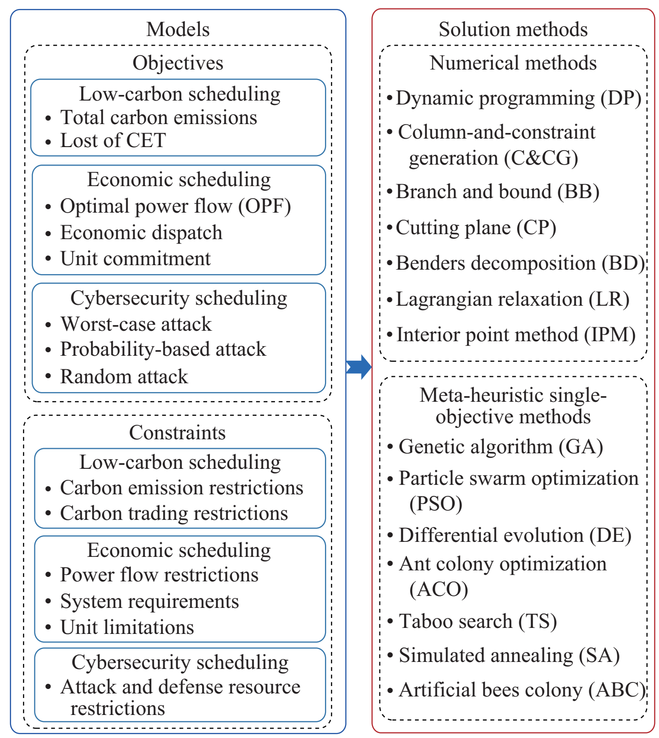

Fig. 3. Single-objective scheduling models and solution methods for SGs.

According to different metrics used in the objective function, the models are classified into three types: low-carbon scheduling, economic scheduling, and cybersecurity scheduling. These models usually include the definition of the objective functions and the associated constraints. They are summarized in Table II and are analyzed as follows.

1) The model for low-carbon scheduling. According to Table II, the objective functions of low-carbon scheduling usually minimize the total carbon emissions and costs of CET [35] - [37]. The related constraints usually include carbon emission restrictions and carbon trading restrictions.

2) The model for economic scheduling. The scheduling problems under the economy metrics encompass OPF, economic dispatch, and unit commitment [38]. OPF enables power grid to establish secure and economic operating states of the system, which is often conducted every 5 min. The economic dispatch is to minimize the overall fuel cost with planning horizons ranging from 1 to 4 hours ahead. Unit commitment aims to optimize the on/off statuses of generating units, which often operates over a more extended time period than OPF and economic dispatch such as 24 hours in advance for day-ahead unit commitment. It can be observed from Table II that the objective functions of the economic

scheduling usually minimize the total cost of power generation and start-up/shut-down actions [20], [22]. The constraints generally include power flow restrictions (e.g., voltage limits, transmission line capacity limits, and nodal power balance limits), system requirements (e.g., power balance, reserve requirements), and unit limitations (e.g., generation output, ramping rate).

TABLE II
OBJECTIVE FUNCTIONS AND CONSTRAINTS UNDER DIFFERENT METRICS

Model	Objective		Constraint	
	Type	Function	Type	Function
Low-carbon scheduling	Carbon emissions	$\min \sum_{m=1}^{M}\sum_{t=1}^{T}E_m(P_{m,t}^{TG})$, where $E_m(P_{m,t}^{TG})=a_m+\beta_m P_{m,t}^{TG}+\gamma_m (P_{m,t}^{TG})^2$	Carbon emission restrictions	$E_0+E_b-E_s\geq \sum_{m=1}^{M}\sum_{t=1}^{T}E_m(P_{m,t}^{TG})$
	CET	$\min C_{\text{CET}}$, where $C_{\text{CET}}=\pi_b E_b-\pi_s E_s$	Carbon trading restrictions	$0\leq E_b\leq E_b^{\max}$, $0\leq E_s\leq E_s^{\max}$
Economic scheduling	OPF	$\min \sum_{m=1}^{M}\sum_{t=1}^{T}C_m(P_{m,t}^{TG})$, where $C_m(P_{m,t}^{TG})=a_m+b_m P_{m,t}^{TG}+c_m (P_{m,t}^{TG})^2$	Power flow restrictions	$V_i^{\min}\leq V_{i,t}\leq V_i^{\max}$, $-P_{i,j}^{\max}\leq \frac{\theta_i-\theta_j}{X_{i,j}}\leq P_{i,j}^{\max}$, $P_i^G-P_i^D=V_i\sum_{j=1}^{N_{\text{bus}}}V_j(G_{ij}\cos\theta_{ij}+B_{ij}\sin\theta_{ij})$
	Economic dispatch	Similar to OPF	System requirements	$\sum_{m=1}^{M}P_{m,t}^{TG}=P_{L,t}+P_{loss}$, $\sum_{m=1}^{M}SR_{m,t}^{TG}\geq SR_t$, $\sum_{m=1}^{M}OR_{m,t}^{TG}\geq OR_t$
	Unit commitment	$\min \sum_{m=1}^{M}\sum_{t=1}^{T}[U_{m,t}^{TG}C_m(P_{m,t}^{TG})+U_{m,t}^{TG}(1-U_{m,t-1}^{TG})\cdot SU_{m,t}^{TG}+U_{m,t-1}^{TG}(1-U_{m,t}^{TG})\cdot SD_{m,t}^{TG}]$	Unit limitations	$P_m^{\min}\leq P_{m,t}^{TG}\leq P_m^{\max}$, $P_{m,t}^{TG}-P_{m,t-1}^{TG}\leq RU_m$, $P_{m,t-1}^{TG}-P_{m,t}^{TG}\leq RD_m$
Cybersecurity scheduling	Worst-case attack	$\max_{\boldsymbol{q}}\left(\min_{\boldsymbol{d}}\sum_{j=1}^{J}u_j(\boldsymbol{d})q_j\right)$	Attack and defense resource restrictions	$0\leq q_j\leq 1$, $\sum_{j=1}^{J}q_j=1$, $p_n=\mathcal{P}_n(d_n)$, $0\leq p_n\leq 1$, $\sum_{n=1}^{N}d_n\leq d_{\text{prevent}}$
	Probability-based attack	$\max_{\boldsymbol{q}}\left(\min_{\boldsymbol{d}}\sum_{j=1}^{J}P(Y_j>y_{\min})q_j\right)$		
	Random attack	$\min_{\boldsymbol{d}}\frac{1}{J}\sum_{j=1}^{J}u_j(\boldsymbol{d})$		

3) The model for cybersecurity scheduling. As shown in Table II, the cybersecurity scheduling can generally be formulated as a min-max optimization problem (OP), where the attacker targets the weakest-/highest-value node with the limited attack resources to cause the maximum system loss, while the defender aims to guarantee the security level of the system by deploying the limited defense resources [39], [40]. The constraints generally include attack and defense resource restrictions.

For these scheduling models, the corresponding solution methods summarized in Fig. 3 can be divided into numerical methods and meta-heuristic single-objective methods. The merits and deficiencies of these methods are comparatively summarized in Table III, while the key observations are discussed as follows.

1) Numerical methods. Numerical methods mainly include DP [41], C&CG [42], BB [43], CP [44], BD [45], LR [46], and IPM [47], which solve OPs by using analytical techniques to find the optimal solutions [22]. It is evident from Table III that most mathematical methods have desirable analyticity and accuracy, but they are often time-consuming due to the complex convexification and/or decomposition processes.

2) Meta-heuristic single-objective methods. Different from numerical methods, meta-heuristic single-objective methods adopt a multi-point random migration strategy in the whole solution space [24]. The most popular meta-heuristic single-objective methods mainly include GA [48], PSO [49], DE [50], ACO [51], TS [52], SA [53], and ABC [54]. As shown in Table III, although most meta-heuristic single-objective methods have fast convergence speeds, they lack stability and easily fall into a local optimum.

B. Multi-objective Optimization

Similar to single-objective optimization elaborated in Section II-A, multi-objective optimization studies can also be grouped into the models and solution methods as shown in Fig. 4.

Specifically, based on the optimization metrics used in the cost function, the multi-objective scheduling models can be grouped into four categories: low-carbon and economy [55], economy and cybersecurity [56], low-carbon and cybersecurity [57], as well as low-carbon, economy, and cybersecurity [58], [59]. These multi-objective scheduling models can be described by the following unified formulation:

TABLE III
MERITS AND DEFICIENCIES OF SINGLE-OBJECTIVE SOLUTION METHODS FOR STANDARD SCHEDULING PROBLEM

Taxonomy	Method	Merit	Deficiency
Numerical method	DP	Effective for multi-stage OPs	Potential challenge related to the curse of dimensionality
	C&CG	Effective for two-stage OPs	Slow convergence
	BB	High efficiency	Poorly suited for large-scale OPs
	CP	Relatively low computational cost	Multiple iterations
	BD	Well suited for large-scale OPs	Slow convergence
	LR	Well suited for OPs with complex constraints	Easy to oscillate in calculation
	IPM	Fast convergence and suitable for OPF	Not suited for discrete or non-convex OPs
Meta-heuristic single-objective method	GA	Strong robustness, good scalability	Low calculation efficiency
	PSO	Easy to adjust parameters	Premature convergence and easy to fall into local optimum
	DE	Strong robustness and fast convergence	Easy to fall into search stagnation
	ACO	Well suited for combinatorial OPs	Slow convergence
	TS	Excellent climbing ability	Non-parallel search
	SA	Simple structure and strong global search capability	Sensitive to temperature parameters
	ABC	High flexibility and few control parameters	Premature convergence

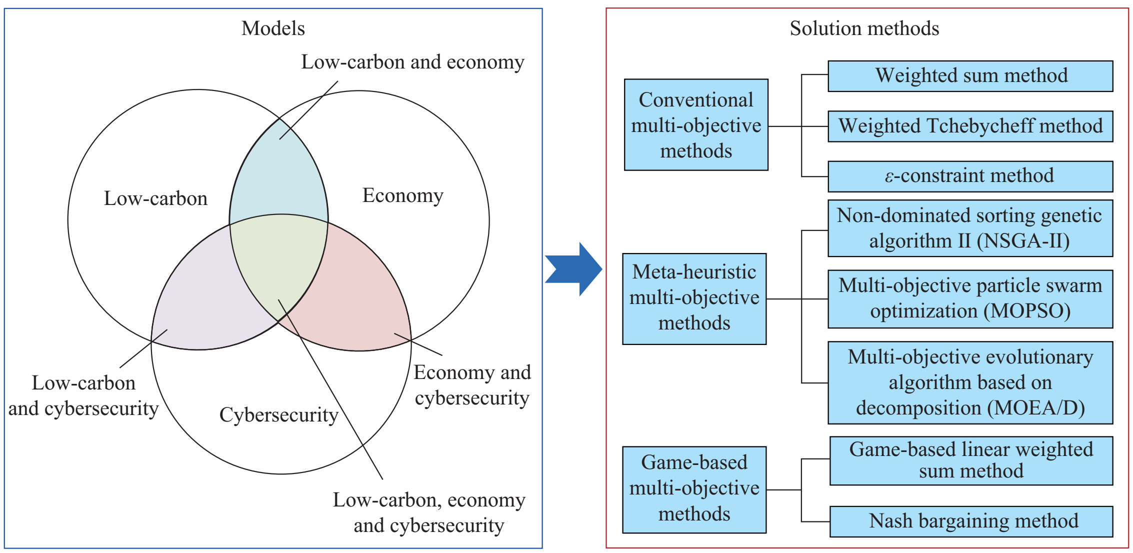

Fig. 4. Multi-objective scheduling models and solution methods for SGs.

$$\begin{cases} \min\limits_{\boldsymbol{x}} \left(f_1(\boldsymbol{x}), \ldots, f_k(\boldsymbol{x}), \ldots, f_K(\boldsymbol{x})\right) \\ \text{s.t. } h_l(\boldsymbol{x})=0 \quad l=1,2,\ldots,L \\ \quad\;\; g_q(\boldsymbol{x})\leq 0 \quad q=1,2,\ldots,Q \end{cases} \tag{1}$$

For the above-mentioned multi-objective scheduling models, the corresponding solution methods can be grouped into conventional multi-objective methods, meta-heuristic multi-objective methods, and game-based multi-objective methods, as shown in Fig. 4. Their merits and deficiencies are summarized in Table IV, which are discussed as follows.

1) Conventional multi-objective methods. Conventional multi-objective methods mainly include the weighted sum method, weighted Tchebycheff method, and ε-constraint method, which usually transform multi-objective optimization into single-objective optimization by applying the weights/parameters on the cost function terms to obtain the optimal solutions [60]. It is evident from Table IV that conventional multi-objective methods are simple to implement, but the choice of weights/parameters could be subjective and reliant on the judgment of the decision-makers.

2) Meta-heuristic multi-objective methods. Meta-heuristic multi-objective methods, which do not require pre-determined weights, dynamically adjust the search direction of the solution to uncover the Pareto front as much as possible. The most popular meta-heuristic multi-objective methods are NSGA-II [61], [62], MOPSO [63], and MOEA/D [64]. From Table IV, although meta-heuristic multi-objective methods have a fast convergence speed, they perform poorly on large-scale OPs.

3) Game-based multi-objective methods. Game-based multi-objective methods aim to address multiple interrelated and competing objective functions through cooperativity and equilibrium [40]. As summarized in Table IV, game-based multi-objective methods can overcome the deficiencies of the subjectivity in choosing the weights, but they are only applicable to the limited types of objective functions in comparison with the above conventional and meta-heuristic multi-objective methods.

TABLE IV
MERITS AND DEFICIENCIES OF MULTI-OBJECTIVE SOLUTION METHODS FOR STANDARD SCHEDULING PROBLEM.

Taxonomy	Method	Merit	Deficiency
Conventional multi-objective method	Weighted sum method	Simple to implement	Determination of weights is usually subjective
	Weighted Tchebycheff method	Simple and intuitive	Easy to fall into local optimum
	ε-constraint method	Suited for convex and non-convex functions	Depending on the chosen constraint bound ε_k
Meta-heuristic multi-objective method	NSGA-II	Fast convergence	High complexity for high-dimensional OP
	MOPSO	Robust searching ability	Sensitive to parameters
	MOEA/D	Low computational complexity	Non-uniform distribution for high-dimensional OPs
Game-based multi-objective method	Game-based linear weighted sum method	Impermeable to subjective influences of decision-makers	Requiring the objective function to be linear
	Nash bargaining method	Reasonable Pareto solutions	Requiring multi-objective function to be convex

C. Cooperative Optimization and Scheduling of SGs Integrated with EVs

To reduce carbon emissions and promote sustainable development, the number of EVs has increased dramatically, and their access to the service market in SGs has drawn substantial interest in recent years. For example, it was reported that Tesla gained USD 554 million from carbon trading in the third quarter of 2023 [65], while BYD in China accumulated over 4.5 million carbon credits with an estimated value of USD 703 million in 2023 [66].

However, the growing demand for large-scale EV charging increases the stress on the power system, inducing adverse impacts on the operational efficiency and power quality. To address the concerns, the cooperative optimization and scheduling for SGs and EVs have been intensively investigated to dynamically adjust the EV charging behavior for ensuring power system stability. The methods developed so far can be categorized into three types: cooperative planning of charging stations, cooperative formulation of charging tariffs, and cooperative scheduling of SGs and EVs.

Considering charging friendliness and load balancing, cooperative planning of the charging stations within SGs in terms of the layout and configuration is the primary issue, because they directly affect the utilization efficiency of EVs and power system stability. The existing works on the charging station planning can be classified into two categories, reflecting the interests of single stakeholder (e. g., the power system, device investor, and EV user) or multiple stakeholders. Most literature focuses on the charging station planning based on the interests of a single stakeholder. For example, with respect to power system security constraints such as voltage, capacity, and load factor, the main objective of the charging station planning is to optimize the operational benefits, carbon emissions, and power losses to further guarantee system stability [67], [68]. For charging device investors, economy is a primary concern, such as investment costs, operating costs, maintenance costs, disposal costs, returns on investment, and long-term benefits. Therefore, the factors such as market demand, charging station utilization, and incentive policies for the power system are often considered during the planning process to maximize investment returns and further promote charging friendliness and load balancing [69]-[71]. Unlike the power system and device investors, EV users primarily focus on the economy and convenience aspects of the charging stations. While meeting their charging demands, they expect the lowest charging costs, the shortest distance, the least charging time, multiple charging power options, and intelligent features to improve the utilization efficiency of EVs [72]. On the other hand, the cooperative planning of charging stations based on the interests of multiple stakeholders has also drawn much attention in recent years, with the aim of addressing the potential conflicts of interest among different stakeholders to further guarantee load balancing. For example, considering the interests of investors and EV users, a bi-level planning model including economic costs, charging queuing time, distance traveled, desired charging volume, and actual charging volume is proposed to improve customer satisfaction and increase the utilization efficiency of EVs [73]. Considering the interests of both the government and charging station operators, a nonlinear non-convex bi-level model based on the perspective of maximizing social welfare is proposed, which is solved via an improved PSO to decrease the payback period and guarantee system stability [74].

Apart from the charging station planning, it is also of practical importance to formulate the cooperative charging tariffs to guide the optimal spatial-temporal allocation of the charging resources, thereby achieving load shifting and guaranteeing system stability. The International Renewable Energy Agency has identified user incentive-based dynamic tariff as a key component in enhancing the flexibility of EVs, which will be crucial for their effective integration into future SGs [75]. According to the results of load shifting, the existing dynamic charging tariff strategies can be categorized into three types: temporal load shifting-based dynamic charging tariffs, spatial load shifting-based dynamic charging tariffs, and spatial-temporal load shifting-based dynamic charging tariffs. Most research works focus on temporal load shifting-based dynamic charging tariffs, which incentivize EVs to adjust their charging time, thereby shifting electricity consumption from peak to off-peak hours [76], [77]. The cooperative formulation of spatial load shifting-based dynamic tariffs focuses on incentivizing the balanced allocation of the charging resources by regulating the tariffs of the charging stations with varying load levels, thereby maintaining system stability and reducing the costs for EVs [78]. Moreover, some studies have focused on the cooperative formulation of spatial-temporal dynamic charging tariffs to improve the utilization rate of the charging stations and guarantee the balanced charging [79].

Assisted with the optimal charging station planning and dynamic tariff formulations, the cooperative scheduling of power output and EV charging/discharging will be able to smooth the peak-to-valley difference, maintain power balance, and achieve low-carbon goals or economic benefits. For example, according to the mechanism of compensating EV battery degradation costs through CET revenues, the CET costs are incorporated into the objective functions to determine the optimal charging and discharging strategies [80]. Furthermore, the integration of EVs and RESs not only improves energy utilization efficiency but also enhances emission reduction benefits, which supports green transition and promotes the holistic approach to decarbonize the power and transport sectors [81]. Combining the flexibility of EVs with RESs, the CET and incentive costs are incorporated into the optimal scheduling model for an integrated electric-hydrogen energy system, where an orderly charging and discharging strategy is then designed by time-of-use tariffs to optimize the economic and environmental performances [82]. The carbon emission costs and load mismatch penalties are also incorporated into a low-carbon scheduling model, which yields a minimum carbon intensity charging strategy to absorb excess wind power and further guarantee power balance [83]. The peak shaving and valley filling are incorporated into a dynamic economic scheduling model, which produces the optimal strategy for online unit generation and the orderly charging and discharging of plug-in EVs [84]. The costs of EVs are incorporated into a two-stage short-term economic scheduling model by using V2G technology, which is solved by using a novel real-coded genetic algorithm to guarantee the balance between supply and demand [85]. Similarly, the integration of EVs with RESs can reduce the reliance on traditional fossil fuels, while lowering both the charging costs and grid operating expenses. To reduce negative impact of output fluctuations of RESs, the charging costs for EVs and the load and generation imbalance caused by the uncertainties in RESs are incorporated into the objective functions, yielding an optimal charging strategy [86]. Finally, a multi-objective dynamic economic emission scheduling model is designed to derive an optimal charging and discharging strategy for EVs to achieve the peak shaving of power grid [87].

III. Distributed Cooperative Control of SGs Considering EVs

Optimal scheduling produces the decision results that will then be achieved by adopting suitable control strategies. This section will first compare the centralized and distributed cooperative control methods that are widely used to implement the optimal scheduling results. Then, two typical distributed cooperative control methods in SGs are analyzed in detail. Finally, distributed cooperative control for SGs and EVs is specifically reviewed.

A. Comparison Between Centralized and Distributed Cooperative Control

The central controller in centralized control can achieve accurate control performance based on the current states of the global system and the decision results from optimal scheduling [88]. However, it has some deficiencies such as high dependence on the central controller and a single point of failure [89], [90].

Unlike centralized control, each controller in distributed cooperative control independently produces the control actions based on the current states of local system and the decision results from optimal scheduling [91]. It presents the merits of excellent scalability, high flexibility, and low communication burden [28]. The distributed cooperative control methods can be further divided into centralized-distributed and autonomous-distributed cooperative control methods, where their merits and deficiencies are comparatively summarized in Table V.

TABLE V
Comparison and Analysis of Centralized-distributed and Autonomous-distributed Cooperative Control Methods

Method	Merit	Deficiency
Centralized-distributed cooperative control	• Accurate control strategy • Simplified coordination	• Single point of failure • Dependent on control center
Autonomous-distributed cooperative control	• High flexibility • Strong robustness	• Difficult to coordinate • Increase in complexity

B. Centralized-distributed Cooperative Control

The centralized-distributed cooperative control architecture for SGs is shown in Fig. 5, where DoS is short for denial of service; FDIA is short for false data injection attack; and RA is short for replay attack.

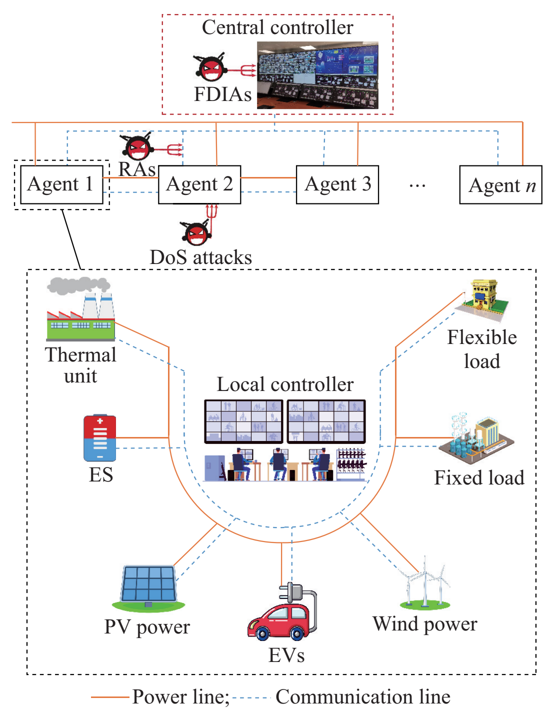

Fig. 5. Centralized-distributed cooperative control architecture for SGs.

Leveraging the advantages of both centralized and distributed cooperative controls, the centralized-distributed cooperative control architecture exchanges information and closely cooperates between central controller and local controllers to guarantee the optimal operation of the whole system. After central controller collects the current states of the system, the dynamic global control strategy is produced and operated by local controllers.

After the optimal scheduling decision results of SGs with EVs are produced based on low-carbon, economy, and cyber-security metrics, they are implemented by centralized-distributed cooperative control. However, the control actions may be interrupted by the attacker due to the tight integration of physical and communication layers in SGs, leading to control performance degradation or even system crash [92]. Depending on whether cyber-attacks are considered in the controller design, the centralized-distributed cooperative control can be further grouped into two categories, i. e., traditional centralized-distributed cooperative control and secure centralized-distributed cooperative control.

Most of the existing methods fall into the first category (i. e., traditional centralized-distributed cooperative control), which is designed based on economy and low-carbon metrics under the attack-free assumption. Two current popular methods are multiagent-based hierarchical hybrid control [93]-[95] and pinning consensus-based control with master controller [96]. In the former framework, the upper level uses a centralized control strategy and the lower level uses a distributed cooperative control scheme, which together achieve the control objective. For the latter, the reference is injected into pinned controllers, which guide local controllers to produce corresponding local control strategies.

For secure centralized-distributed cooperative control, the above traditional centralized-distributed cooperative control methods are re-designed considering possible cyber-attacks. This is because the authentication and integrity of data may be destroyed by cyber-attacks. Currently, there are three typical types of cyber-attacks [10], i.e., DoS attacks, FDIAs, and RAs.

1) Secure centralized-distributed cooperative control under DoS attacks. When the data are transmitted among local controllers or between central controller and local controllers as shown in Fig. 5, they may be subject to DoS attacks, causing data packet dropout. In fact, communication network is divided into different sub-networks, i.e., network topology is dynamically changing because DoS attacks could block communication channels [97]. This will deteriorate system performance and even cause system crash, e.g., when pinned controllers suffer from DoS attacks, the corresponding local controllers without pinning control signals will not have access to the reference, resulting in their frequencies not being restored to the rated value [98], [99]. As a result, the centralized-distributed cooperative control needs to be redesigned by considering the impact of DoS attacks. To deceive the communication between central controller and local controllers, the cunning DoS attacker may intelligently decide to block transmission channels or to lurk in the system [100]. According to whether the model of DoS attacks is known, the control strategies can be classified into secure centralized-distributed cooperative control based on the model of DoS attacks or based on DoS attack detection. For the former, after capturing data packets with network analysis tools (e.g., Ethereal, Airo Peek), the model of DoS attacks can be built by statistical analysis. Furthermore, considering these attack models, secure centralized-distributed cooperative control can be designed [101]. For example, after DoS attacks are modeled as independent Bernoulli processes, a distributed secure fuzzy output-feedback controller is designed to reduce the effect of DoS attacks [102]. DoS attacks are modeled based on the idea of persistence of data flow, and a secure edge-based self-triggered controller is designed to resist multi-layer DoS attacks [103]. In the latter case, when DoS attacks are dynamic and stochastic, they are difficult to model. Alternatively, real-time DoS attack detection is employed, and a secure centralized-distributed cooperative controller can be designed based on the corresponding detection results. For example, DoS attacks are detected by matching the communication frequency with the predefined switching frequency, and the controllers are further isolated to maintain secure operation of the system [104].

2) Secure centralized-distributed cooperative control under FDIAs. FDIAs mean that the attacker can inject false data into central and/or local controllers as illustrated in Fig. 5, which can change the authenticity of data and result in wrong control commands [105]. It will deteriorate system performance and even cause the system to collapse, e.g., the state error fails to converge to zero, making the system deviate from the desired operating status [106]. Similarly, the existing control methods in this area can be further classified into secure centralized-distributed cooperative control based on FDIA models and FDIA detection methods. For example, FDIAs are described by Bernoulli distribution, and an H_∞ load frequency controller is developed to guarantee system to be exponentially mean-square stable in the power system [107]. After FDIAs are detected via a disagreement Laplacian potential-based algorithm, a secure controller with a logical evaluation scheme is designed to maintain system performance [108].

3) Secure centralized-distributed cooperative control under RAs. RAs usually steal previous sensor data or control commands and inject them into the system as shown in Fig. 5, which could produce wrong control commands, deteriorate the overall system performance, and even cause the system to collapse [109]. The existing control methods can be classified as secure centralized-distributed cooperative control based on the model and detection results of RAs. For example, RAs can be formulated as a time shift, and the controller with a Luenberger-like observer is then designed to improve system security [110]. After RAs are detected by a threshold-based neighbor observation mechanism, a secure controller with marginalization and isolation mechanisms is designed to enhance system performance [111].

C. Autonomous-distributed Cooperative Control

The autonomous-distributed cooperative control architecture for SGs is shown in Fig. 6. Unlike centralized-distributed cooperative control, the autonomous-distributed cooperative control architecture does not need a central controller, where local controllers communicate and cooperate with each other to achieve the optimal operation of the whole system. After local controllers collect the real-time states of neighboring controllers, the control strategy is dynamically adjusted based on the cooperation or negotiation among local controllers.

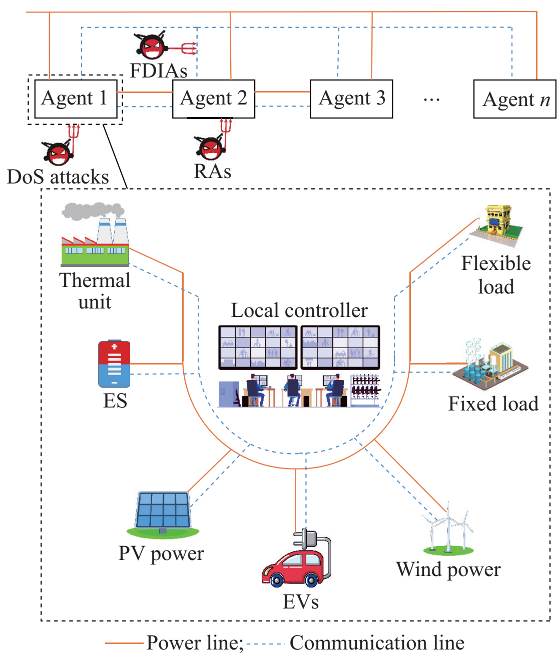

Fig. 6. Autonomous-distributed cooperative control architecture for SGs.

After the optimal scheduling decision results are produced based on low-carbon, economy, and cybersecurity metrics, they are achieved by autonomous-distributed cooperative control to complete the optimal objectives. Similarly, considering the impact of cyber-attacks, the existing control methods on this topic can be divided into traditional autonomous-distributed cooperative control and secure autonomous-distributed cooperative control.

The traditional autonomous-distributed cooperative control in attack-free cases is usually designed based on economy and low-carbon metrics. The current popular methods include consensus-based algorithm [112], [113] and model predictive control (MPC) [114], [115], etc.

Secure autonomous-distributed cooperative control can be divided into three categories based on its re-designs against DoS attacks, FDIAs, and RAs.

1) Secure autonomous-distributed cooperative control under DoS attacks. The existing control methods can be classified into secure autonomous-distributed cooperative control based on the model or detection result of DoS attacks. For example, DoS attacks are modeled as a Markov chain, and a cyber-resilient controller is designed to enhance the attack-resilient capability of the system [116]. After DoS attacks are formulated as a Bernoulli distribution, an event-triggered model-free predictive controller is proposed to improve control performance [117]. DoS attacks are detected by deep neural networks, and a secure controller with compensation mechanisms is designed to mitigate the effect of DoS attacks [118].

2) Secure autonomous-distributed cooperative control under FDIAs. According to the model or detection result of FDIAs, a secure controller can be designed to guarantee system performance. For example, FDIAs are modeled as a Bernoulli distribution, and a secure sliding mode controller is developed to resist multilink FDIAs [119]. After FDIAs are detected by artificial neural networks, an MPC-based controller is designed to improve system performance [120]. FDIAs are detected by a bi-directional long short-term memory neural network, and proportional-integral-derivative controller parameters are optimized by an improved whale optimization algorithm [121]. After FDIAs are detected based on Kullback-Liebler divergence criterion, a secure controller with trust mechanisms is designed [122]. After FDIAs are detected, a secure distributed economic model predictive controller is designed to perform load frequency control of SGs participating in large-scale plug-in EVs [123].

3) Secure autonomous-distributed cooperative control under RAs. Similarly, a secure autonomous-distributed cooperative controller can be designed based on the model or detection result of RAs. For example, RAs are described by time shift, and a secure controller with an active moving target defense strategy is proposed to improve system performance [124]. After RAs are detected by distributed Kalman filter observers, a secure controller with isolation mechanisms is designed to counteract the negative impacts of RAs [125].

D. Distributed Cooperative Control for SGs and EVs

With the widespread integration of EVs into SGs, their centralized charging behavior inevitably leads to local capacity overloading, which triggers frequency and voltage anomalies and thereby affects the stability of the power system. To address this problem, distributed cooperative control methods for SGs and EVs are proposed, which aim to achieve dynamic regulation of frequency and voltage, thus guaranteeing system stability. The existing studies on distributed cooperative control for SGs and EVs can be roughly categorized into two types, according to whether the issue to be addressed is related to frequency or voltage regulation.

In SGs, EVs can be used not only as controllable charging loads, but also as mobile ES devices to participate in frequency regulation, benefiting the stable operation of the power system. For example, to improve the dynamic frequency regulation capability of EVs connected to an uninterruptible-power AC microgrid, a consensus-based cooperative adaptive virtual inertia strategy is proposed to suppress power oscillation [126]. To manage frequency irregularities, a distributed controller based on MPC and adaptive droop control is proposed, which effectively controls EVs during huge changes in loads to achieve the efficient operation of the microgrid [127]. A novel distributed frequency controller based on a resource-efficient event-based broadcast mechanism is developed to address secondary frequency regulation of power grid under V2G supplementary service [128]. Considering the control and coordination of EVs and wind power, an autonomous distributed cooperative controller is designed to regulate the frequency of the microgrid [129].

Similar to the above cooperative frequency regulation, when the distribution network voltage fluctuates, power grid and EVs achieve bidirectional power regulation through distributed cooperative control methods, thus guaranteeing the stability of grid voltage. For example, combining EVs and PV power into a medium-voltage distribution network, a distributed cooperative controller based on a consensus algorithm is designed to regulate the voltage quality [130]. According to the incremental costs, an improved discrete-time leader-following consensus control method for EVs participating in demand response is proposed to achieve the total power balance and the stability of charging-side voltage [131]. To address the voltage regulation problem, a distributed voltage control algorithm based on MPC is proposed, which coordinates active and reactive power compensations from PV inverters and EVs [132]. To solve the problem of cooperative active and reactive power control in EVs, a multi-agent reinforcement learning algorithm based on deep deterministic policy gradient and parameter-sharing framework is proposed, which achieves demand-side response and voltage regulation [133].

In summary, some research efforts have tried to address optimal scheduling and distributed cooperative control for SGs integrating EVs. To present representative methodologies in this domain, Table VI provides an overview of relevant studies, detailing their methods, research objectives, and key findings. As shown in Table VI, most existing optimal scheduling and distributed cooperative control methods only partially consider the comprehensive set of low-carbon, economy, and cybersecurity metrics.

TABLE VI
SUMMARY OF REPRESENTATIVE STUDIES ON OPTIMAL SCHEDULING AND DISTRIBUTED COOPERATIVE CONTROL METHODS FOR SGS WITH EVS

Ref.	Method	Research objective	Key finding
[41]	Stochastic dual DP	Enhancing economic dispatch flexibility and robustness under uncertainty, while improving renewable energy accommodation	Reduce total cost by 14%-19%, and cut renewable energy curtailment from 4225.98 MWh to 1191.08 MWh by virtual ESs
[48]	Improved GA for unit commitment/economic dispatch	Enhancing accuracy and efficiency in unit commitment and dispatch under nonlinear constraints	Achieve cost within 2% of the reference solution, with improved feasibility and faster convergence
[61]	Global NSGA-II	Improving the evenness of Pareto set	Reduce pollutant emissions in Scenarios 2-4 by 54.78%, 19.05%, and 71.45%, respectively, compared with that in Scenario 1
[80]	Actual coded GA	Offsetting plug-in EV battery degradation costs through carbon trading incentives	Achieve full offset of battery degradation cost when the carbon trading price is 0.07 $/kg or 0.08 $/kg
[85]	Mean-variance mapping optimization	Coordinating plug-in EV as active participants while considering battery degradation, user preferences, and grid limits	Improve energy exchange efficiency and increase economic benefits by up to 121%
[87]	DE algorithm	Reducing both emissions and total cost in wind-EV integrated dispatch	Achieve a total cost of $\$2.43\times10^6$ and carbon emissions of approximately 1.18×10^5 kg, significantly outperforming other algorithms
[102]	Fuzzy output-feedback controller	Designing an attack-resilient distributed fuzzy load frequency control method	Tolerate a maximum physical DoS attack probability of approximately 0.6
[104]	Switching frequency-based detection mechanism	Developing a control strategy ensuring accurate frequency restoration and system stability under cyber-attacks	Have robustness against DoS attacks involving the disruption of up to three communication links
[107]	H_∞-based proportional-integral (PI) controller	Guaranteeing robust frequency regulation and desired closed-loop performance in the presence of FDIAs	Enable system frequency deviation to return to a stable state within 4 to 5 s under FDIAs
[114]	Hybrid MPC	Achieving accurate current sharing among distributed generation units to enhance load balancing and system stability	Reduce the steady-state settling time by approximately 87.5% compared with the conventional MPC, achieving convergence within just 0.05 s
[124]	Converter-based moving target defense strategy	Enhancing the detectability of RAs in microgrids without compromising voltage stability	Detect RAs almost immediately upon activation and restore system operation
[128]	Resource-efficient event-based broadcast mechanism	Designing a frequency regulation method adaptive to time-varying network conditions for V2G-based secondary frequency control	Maintain the frequency deviation within a tolerable range in the presence of communication decay/failures
[134]	Bi-level optimization with improved PSO	Reducing carbon emissions and economic cost	Reduce the total operating cost by 71.11% and total carbon emissions by 49 kg
[135]	Quantum-classical BD	Reducing the time and space complexity of stochastic dispatch in renewable-rich system	Significantly reduce scenario generation time and computational complexity while achieving efficient stochastic dispatch
[136]	Hybridization of PSO and gravitational search algorithms	Achieving substantial cost reductions	Reduce the monthly energy cost by $60720, from a base case value of $94551

IV. Application of Optimal Scheduling and Distributed Cooperative Control in SGs: From Theory to Practice

Optimal scheduling and distributed cooperative control of SGs considering EVs have found several real-world applications, and eight representative examples are summarized in Table VII. In Table VII, A1 is an example of optimal scheduling for SGs with RESs in Xinjiang, China, where a low-carbon economic scheduling scheme integrating CET is employed, thereby improving the operational efficiency of the system [37].

TABLE VII
Several Representative Real-world Applications of Optimal Scheduling and Distributed Cooperative Control

Ref.	No.	Name and location	Scale	Method	Result
[37]	A1	Dispatching system for integrated wind-PV-thermal power in Xinjiang, China	• The supporting power supply was composed of 6844 MW wind power, 1150 MW PV power, and 5280 MW thermal power in Tianzhong • There are 3138 MW of PV power, 4830 MW of thermal power, and 149 MW of wind power in Taklimakan desert	A low-carbon economic scheduling model incorporating CET and RESs is proposed to guarantee the efficient operation of the system	• CET can promote the optimization of energy structure • Increasing the carbon trading price will not only effectively reduce carbon emissions, but also promote the consumption of RESs
[137]	A2	Economic and environmental operation management in Athens, Greece	• Two PV generators with capacities of 1.1 kWp and 4.4 kWp • Two battery storage systems with a total capacity of 80 kWh • A resistive load bank with a maximum active power of 13 kW	An economic and environmental operation management approach based on two-stage stochastic programming is proposed to minimize both the emissions and operational costs	• The proposed stochastic control framework is feasible and more effective than the deterministic approach, enabling a flexible trade-off between emissions and costs
[138]	A3	Charging station planning for Yizhuang New Town in Beijing, China	• The total area is around 225 km^2 • There will be 870000 permanent residents in Yizhuang, and traffic with the other regions of Beijing is expected to increase after 2035 • There are approximately 16000 EVs	A charging station planning model that considers the spatial-temporal characteristics of EV charging demand is proposed to minimize the total costs while satisfying the constraints of both suppliers and drivers	• The proposed model can effectively satisfy the charging demand and minimize the wastage of the charging resources • When EV penetration exceeds 50%, the operation safety of power grid may be jeopardized
[139]	A4	EV charging station planning in Pretoria, South Africa	• The charging station opening hours are 09:00-22:00 • Saturday experiences the highest demand of 697 kW	A multi-objective scheduling model for the charging station planning is developed to improve economic returns and user satisfaction	• The proposed planning strategy improves weekly profit by 19% and user satisfaction by 14% • The proposed scheduling strategy achieves a 14% reduction in maximum demand costs
[140]	A5	EV charging scheduling optimization for a solar-based grid-tied charging station (SGTCS) in Islamabad, Pakistan	•The charging station can simultaneously serve 250 EVs including 75 high-power EVs rated at 150 kW and 175 low-power EVs rated at 50 kW • The SGTCS consists of a 1000 kW PV system and a 774 kW PV converter, and is equipped with six 150 kW charging slots	An EV charging scheduling optimization strategy is proposed for SGTCS, which is implemented by using the HOMER Grid tool to improve PV utilization and reduce carbon emissions	• The PV system supplies 64.5% of the annual energy (1752305 kWh), with the remaining 34.5% drawn from the grid • The proposed SGTCS has a carbon footprint of 310729 kg/year, significantly lower than that of the system without renewable energy (1190387 kg/year)
[141]	A6	Cooperative scheduling of EVs for low-voltage residential grids in Sydney, Australia	• The feeder operates radially with a nominal phase-phase voltage of 400 V and supplies 42 detached residential buildings • There are 15 houses equipped with EVs	A cooperative management system of EVs and low-voltage residential grids is proposed to minimize economic cost	• The proposed scheduling strategy prevents any undervoltage instances • The proposed scheduling strategy reduces economic cost and guarantees system stability
[142]	A7	Distributed resource control (e.g., EV charging stations) for secondary frequency response at the University of California, San Diego, USA	• There exists a 69 kV substation and a 12 kV radial distribution network that serves the entire 5 km^2 campus of the University of California • Over 200 EV chargers, comprising unidirectional V2G (V1G) and V2G units	A distributed cooperative control strategy for coordinating heterogeneous distributed energy resources in secondary frequency regulation is proposed to improve economic viability through participation in ancillary service markets	• The proposed strategy allows distributed energy resources to track the active power reference • Economic analysis confirms market eligibility and estimates up to $53000 in annual revenue for the selected distributed energy resources
[143]	A8	Distributed cooperative frequency regulation of EVs and power grid in Qingyuan, China	• The daily service volume of each charging station is 75 • The daily service volume of each battery swapping station is 50 • The charging efficiency of each EV is 0.95	A distributed cooperative frequency regulation method involving EV participation in power grid is proposed to guarantee system stability	• The proposed method guarantees the balance of system frequency stability and economic efficiency • EV-based virtual synchronization enhances inertia and limits frequency drift

A2 is an example of economic and environmental optimal scheduling in Athens, Greece with the objective of minimizing carbon emissions and operational costs [137]. A3 and A4 are two examples of cooperative optimization for SGs with EVs in Beijing, China and Pretoria, South Africa, which propose the charging station planning methods from the perspective of operational costs or user satisfaction [138], [139]. A5 and A6 are the examples of the cooperative scheduling for SGs with EVs in Islamabad, Pakistan and Sydney, Australia, respectively, where the cooperative charging and discharging is employed to reduce carbon emissions and enhance peak shaving and valley filling [140], [141]. A7 is an example of distributed cooperative control in San Diego, USA, in which a control strategy coordinates heterogeneous distributed energy resources (e. g., EV charging stations) for secondary frequency regulation, improving economic viability [142]. A8 is an example of distributed cooperative control for SGs with EVs in Qingyuan, China, where a distributed frequency regulation method involving EV participation in SGs is proposed, thereby guaranteeing system stability [143].

V. Conclusion and Challenging Issues

Due to the topology changes in power systems as well as the widespread deployment of smart meters and intelligent devices with communication functions, optimal scheduling and distributed cooperative control for power grid with significant penetration of EVs have become a research hotspot in recent years. This paper presents a comprehensive literature review on optimal scheduling and distributed cooperative control while considering low-carbon, economy, and cybersecurity metrics. However, several important challenges remain open as summarized in Fig. 7, including optimal modeling, multi-metric game, intelligent detection, active defense, and real-world deployment, with their corresponding research gaps and future directions detailed as follows.

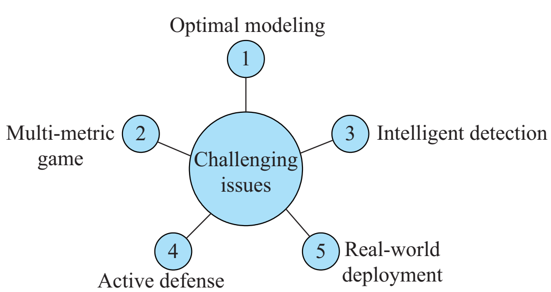

Fig. 7. Summary of challenging issues.

1) Optimal modeling

The existing optimal models usually include the optimal objectives of power grid by primarily considering various related issues such as power outputs and start-up/shut-down of generation units, carbon trading, and power grid constraints. However, these optimal models usually ignore the critical characteristics of the associated communication network, such as network-induced delay and bandwidth. It inevitably affects the effectiveness of optimal scheduling because power grid and communication network are strongly coupled. Moreover, these objectives and constraints will change dynamically because new issues such as cyber-attacks may destroy network topology and data transmission paths, leading to fault cross-propagation between power grid and communication network. Specifically, a large number of smart devices such as EVs, EV charging stations, and smart meters are integrated into SGs, and they may become the targets of cyber-attacks. If these smart devices or communication networks are attacked, the integrity and authenticity of data will be destroyed. It will mislead state estimation or power flow calculation, thereby leading to incorrect scheduling commands and producing system frequency or voltage deviations, etc. It will probably cause cascading failures in power grid and/or communication network, bringing about changes in system topology. Therefore, the existing scheduling models must consider such dynamic cyber-physical coupling changes.

To incorporate these new factors into the scheduling models, it is necessary to adopt hierarchical or co-optimization approaches that jointly model power system operation and cyber-layer constraint. These approaches will offer a more appropriate representation of cyber-physical interaction, enabling the scheduling process to respond dynamically to network-induced uncertainties or topological changes. Therefore, future optimal modeling research can respond to these dynamic issues in the optimization objectives and constraints. Moreover, some network monitoring tools that track some key measures (e. g., delay, data packet loss rate, and structure of network topology) can be developed. It can assist in providing accurate parameter for the optimal model.

2) Multi-metric game

The economy metrics are often considered in the optimal scheduling and distributed cooperative control of the conventional power system, but modern power system with significant penetration of EVs should also consider low-carbon and cybersecurity metrics. These three metrics are not isolated but rather interact in an often competing manner. Due to dynamic and uncertain nature of power system operation, they may exhibit varying degrees of coupling and competition over time, requiring flexible mechanism to balance the trade-offs. For example, when the power system operates in a normal state away from the alert state, economy and low-carbon metrics can be emphasized during the construction process of optimal models, maximizing economic benefits and the utilization of RESs. In contrast, when the power system is approaching an alert state, the cybersecurity metrics become the most important consideration during the construction process of optimal models, to maintain safe running of the system. Moreover, the existing scheduling models generally lack the ability to recognize and respond to the changes in power grid operating states. They are unable to dynamically adjust the trade-offs among optimization objectives based on system risk level or operational phase, which limits their effectiveness under such conditions.

To address these issues, future research can dynamically adjust the relative importance (i. e., the weight) of low-carbon, economy, and cybersecurity metrics, which can be achieved by real-time assessments of grid operational states. To support this process, evolutionary game theory can be used to describe the ongoing competition among these metrics. Compared to static game models, it can better capture dynamic interactions and shifting priorities among competing metrics, which is essential for modeling the trade-off strategies under varying system risk levels and operational conditions.

3) Intelligent detection

With high penetration of EVs in SGs, a large number of smart meters and communication devices are widely deployed to guarantee their efficient operations. However, the open network environment makes SGs with EVs extremely vulnerable to cyber-attacks, particularly at critical nodes such as the charging stations and RES access nodes. The current attack detection methods can only identify the known attacks and typically assume attack behaviors conform to a specific probability distribution. These existing model-based detection methods would fail as the statistical characteristics of the measurement and control data are insensitive to carefully crafted cyber-attacks. Moreover, new cyber-attacks that are of much higher risk than the known cyber-attacks may easily fail the existing supervised learning-based attack detection methods. Further, some deep learning-based approaches are proposed for attack detection, but they often lack interpretability, making it difficult to identify the types and sources of cyber-attacks.

To address these limitations, future research can explore intelligent detection methods that combine domain knowledge with data-driven insights to enhance adaptivity, generalization, and interpretability. For example, hybrid methods that integrate model-based residual analysis with unsupervised learning can help detect novel or stealthy attacks without relying on predefined labels or statistical assumptions. To improve the interpretability of detection results, large language models such as GPT or DeepSeek can also be integrated into detection frameworks to reason about potential causal relationships between cyber and physical layer anomalies and generate human-understandable explanations.

4) Active defense

The attackers may dynamically change their attack strategies based on the known defense control designs, and launch cyber-attacks from different intra-/inter-subsystems in SGs with EVs. Most of the current defense control strategies are designed based on detection results, which can be bypassed because the attacker may quickly adjust their strategies once the defense control strategy is cracked. Moreover, these existing defense control strategies lack early-warning capabilities for potential cyber-attacks, which makes the defense mechanisms ineffective. When cyber-attacks are launched and cause data loss and even tampering, they will drive the operational state of the power system toward an alert or even emergency state due to wrong decision results. Furthermore, most existing defense strategies remain passive and lack the capability to proactively intervene in attack paths or adversarial behaviors.

To overcome the limitations of the existing defense methods, future research may explore proactive security mechanisms. One promising direction involves data protection methods such as the deployment of lightweight encryption protocols and privacy-preserving data sharing schemes, aiming to prevent information exposure across distributed nodes. Another promising direction is to use deception-based techniques (e. g., honeypots and moving target defense) or data confidence based on the above attack detection to enhance system security.

5) Real-world deployment

Most real-world applications of optimal scheduling and distributed cooperative control focus on small-scale systems. However, with the rapid growth of large-scale EVs and RERs, the structure of SGs is becoming increasingly complex. To achieve rapid scalability, future research can adopt modular design principles at both the software and system levels. At the software level, the functions such as the aforementioned optimal scheduling and distributed cooperative control methods are designed as independent modules, which can be scaled horizontally by adding the instances or vertically through computational resource upgrades, without interfering with one another. At the system level, terminal power devices and automation control systems interconnect via communication networks, allowing plug-and-play integration of new devices and supporting the expansion of larger SG topologies across different regions without major redesign. Moreover, to reduce air pollution, some countries around the world are also encouraging the development of RESs and EVs through necessary policies, which will further promote their deployment and guarantee their security.

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