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Review

Resource Modeling, Market Participation, and Coordinated Operation of Virtual Power Plants: A Review

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Abstract

Virtual power plants coordinate distributed energy resources to provide market services, but the value of a scheduling strategy depends on consistency between physical capabilities, market commitments, uncertainty treatment, and participant incentives. This review examines resource modeling, coordinated market bidding, uncertainty-aware scheduling, benefit allocation, and distributed and learning-based implementation. The reviewed approaches are compared by their operating assumptions, information requirements, computational demands, and application limits. Three connections emerge. First, commitments across energy and ancillary-service markets must share the same resource, network, and delivery constraints; adding revenue streams alone does not establish realizable gains. Second, stochastic, robust, and distributionally robust formulations address different information and risk considerations, while rolling-horizon optimization provides a complementary updating framework. Third, the distributable surplus and the incentives for cooperation depend on the dispatch and cost assumptions used to calculate it. Application examples illustrate how these decisions interact. Research priorities include validated aggregate flexibility models, consistent settlement and degradation representations, calibrated out-of-sample risk assessment, and reproducible evaluation of scalable scheduling methods. The review provides conditional guidance for selecting compatible methods; heterogeneous simulation settings limit direct performance rankings and conclusions about field deployment.

Keywords: virtual power plant; optimal scheduling; uncertainty; profit allocation; multi-service

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1. Introduction

Power consumption has steadily increased due to population and economic growth. The fossil fuel-dominated energy system struggles to fulfill electricity demand due to rising energy output and consumption. Excessive fossil energy use worsens global warming, air pollution, and ecological imbalance [1]. The old energy system must be transformed to address energy security and environmental degradation, which threaten sustainable social development. On 22 April 2016, 178 nations signed the Paris Agreement to combat climate change. The pact aims to restrict the world's average temperature rise to far below 2 °C over pre-industrial levels and 1.5 °C [2]. Reducing fossil fuel use and generating clean renewable

energy are important to overcoming these problems. International Energy Agency report: the 2050 energy structure will be more diverse than the current structure under a net-zero emissions scenario [3]. Oil, coal, and natural gas supplied 30%, 26%, and 23% of world energy in 2020. Energy from biomass, wind, solar, hydro, and geothermal sources will supply two-thirds of global energy demand by 2050 [4,5].

China has set "Dual Carbon" targets of peaking carbon emissions by 2030 and carbon neutrality by 2060 [6–8]. Chinese energy structure revolution accelerates with these aims. Figure 1 shows that traditional thermal power installed capacity declined from 65.7% to 43.1% between 2015 and 2024 [9]. Solar and wind power installation capacity grew quickly. Solar power generating capacity rose from 2.8% in 2015 to 26.5% in 2024. The inherent stochasticity, volatility, anti-peaking characteristics, and insufficient regulation capability of wind and solar power remain the main obstacles to large-scale grid integration [10,11]. Traditional thermal power plants must become flexible regulating sources due to high renewable energy integration [12]. The shortage of overall flexible regulation resources in the new power system remains severe despite this role transformation.

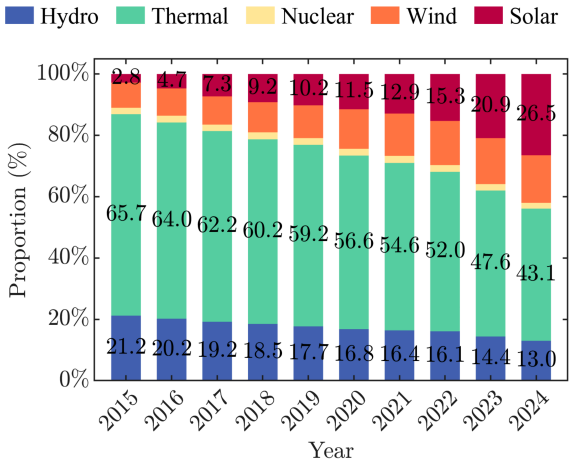


Figure 1. Evolution of the installed capacity proportion in China for different power generation types (2015–2024).

Relying solely on traditional generation-side scheduling is insufficient to address the challenges of renewable energy integration and fails to fully realize environmental benefits. Distributed energy resources (DERs) are considered valuable resources for future energy systems due to their high utilization efficiency, environmental friendliness, operational flexibility, cost-effectiveness, and system resilience enhancement. The inherent low capacity and wide distribution of DERs pose challenges to the safe, stable operation and efficient scheduling management of the power grid [13]. Developing advanced aggregation technologies for efficient multi-source complementary scheduling represents a key pathway to enhancing renewable energy consumption levels. Virtual power plants (VPPs) can transcend physical topology and geographical limitations to integrate dispersed DERs into a coordinated optimization framework. VPPs align with the wide distribution of DERs through flexible grid connection points and large-scale coordination, offering advantages in integrating fragmented resources [14]. By enhancing energy efficiency and renewable energy integration, VPPs are aligned with global development goals, including clean energy, sustainable communities, and responsible production (sustainable development goals 7, 11, and 12). VPPs are established as a primary driver for the advancement of the "Dual Carbon" strategy and the transformation of the energy system. Driven by policy initiatives, academic attention has been increasingly directed toward the aggregated management of heterogeneous DERs. Journal literature was searched in the Web of Science Core Collection using the Topic field and the search terms "virtual power plant" and "VPP", with the search

restricted to the Science Citation Index Expanded. Figure 2 summarizes annual Article and Review counts from 2016 to February 2026, with 934 records for 2025.

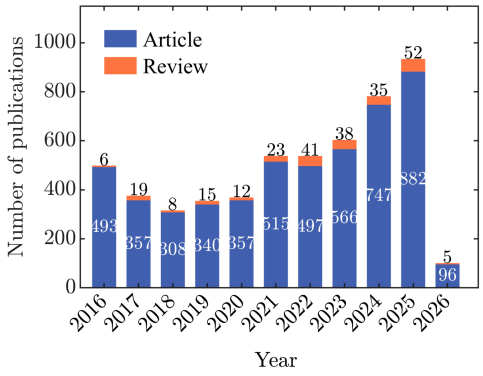


Figure 2. Annual distribution of VPP-related publications in the Web of Science database (2016–February 2026).

Modeling of DERs provides the essential foundation for the operational scheduling of VPPs. A summary of literature reviews focusing on diverse DERs within the VPP framework is provided below. The current status of control, management, and optimization strategies for prosumers, DERs, and small-scale VPPs was presented by Mahmud et al. [15], with research gaps and potential improvements identified. However, the mathematical modeling of DERs was inadequately addressed. Furthermore, a conceptual distinction between VPPs and aggregators is required to prevent terminological confusion. Specific review efforts have focused on individual DER technologies, particularly electric vehicles (EVs). For instance, the optimal scheduling and control methods for EV-based VPPs were explored by Yang and Zhang [16], including detailed classifications, uncertainties, and operational constraints of VPPs. Nevertheless, an analysis of the applicability of existing uncertainty handling methods to the stochastic nature of EVs was missing. Similarly, the concept of VPPs utilizing EVs as the primary aggregation resource was introduced by Inci et al. [17]. That study examined vehicle-to-grid integration topologies in terms of energy generation/storage units, system architectures (single-stage, two-stage, or hybrid multi-stage), and grid-connection parameters. Both aforementioned studies neglected the modeling of DERs other than EVs and lacked discussion on uncertainty optimization methods or internal multi-agent games within the VPP context.

The interaction between VPPs and electricity markets, including carbon markets, is a key research area following uncertainty management. A review focusing on the formulation of VPPs' optimization problems, solution methods, and market participation was provided by Naval and Yusta [18]. In the formulation process, the impact of modeling detail for DERs was ignored. Furthermore, electricity markets were categorized broadly without considering regional locations, time scales, or joint bidding strategies. The concepts, technologies, control, and market operations of VPPs and aggregators were covered by Kaiss et al. [19]. Similar issues to those in [18] were identified, and the impact of uncertainty on VPPs' control and economics was omitted. Modeling methods for carbon flow in VPP operations were evaluated by Wang et al. [20], with an analysis of the coordination between VPPs and electricity markets through carbon trading. Although carbon markets were described, the classification of electricity markets was limited to day-ahead and real-time sectors. Additionally, uncertainty handling methods were restricted to stochastic programming (SP) and robust optimization (RO). A description of the suitability of these methods for different types of uncertainty was not provided.

Research on handling multiple uncertainties within VPPs energy management frameworks has been conducted in various studies. Sources of uncertainty in VPPs research and

practice were categorized by Yu et al. [21] into renewable energy output, market prices, and electricity loads. Mathematical expressions and modeling approaches were provided, and objective functions and constraints in scheduling and trading were summarized. Uncertainty from controllable loads was ignored. The analysis was limited to SP and RO, and a comparison of application boundaries or trade-offs was missing. VPP concepts and energy management applications were introduced by Rouzbahani et al. [22]. Applications were divided into optimization scheduling and uncertainty handling. Scheduling techniques were classified into mathematical programming, heuristic algorithms, and learning-based methods, specifically deep reinforcement learning (DRL). Weaknesses of these algorithms were not identified. While sub-methods of SP and RO were discussed, application boundaries for each were not defined. Internal coordination and external interactions of VPPs were analyzed by Gao et al. [23]. Uncertainty handling methods, control architectures, and market games were reviewed. The analysis was restricted to multiple electricity markets and did not address service differences across regional markets. Although types of uncertainty for optimization scheduling were identified, treatment methods and suitable scenarios require more work. Internal DERs and uncertainty forecasting were the focus of Dogan and Cidem Dogan [24]. Machine learning models were emphasized, but the study was restricted to forecasting. The evolution of DERs modeling and the connection to VPPs optimization scheduling were not analyzed.

Advanced enabling technologies, including artificial intelligence, data analytics, and communication architectures, are required to achieve complex operational and market objectives. The categorization of DERs aggregated by VPPs was introduced by Bhuiyan et al. [25], where the evolution from centralized systems to decentralized artificial intelligence and edge computing was described. Modeling for DERs and multi-energy market participation was missing, which complicates the assessment of integration between technology and optimization. Blockchain applications within VPP components were analyzed by Hong et al. [26], and a development roadmap for performance improvement and system integration was proposed. That work focused on peer-to-peer energy trading and simplified VPP participation in multi-energy markets. Machine learning applications in VPPs and home/building energy management systems were reviewed by Sierla et al. [27]. However, bidding and profit models for multi-energy systems in different markets were oversimplified, creating a gap between the models and actual market conditions. Data-driven energy management applications in VPPs were examined by Ruan et al. [28]. While uncertainty methods were described, the advantages, disadvantages, and limitations of each method were not identified. A detailed classification of cost–benefit analysis and market participation was missing, making it difficult to identify gaps in the existing literature.

This narrative review examines VPP operation through the connections among resource modeling, market bidding, optimization under uncertainty, and benefit allocation. The central question is whether the assumptions adopted at these stages are mutually consistent. Resource models determine the flexibility that can be offered, market rules define delivery obligations and remuneration, uncertainty management influences scheduling decisions and risk exposure, and allocation mechanisms determine how the resulting gains and costs are shared. Accordingly, the reviewed approaches are compared in terms of their physical assumptions, information requirements, computational demands, and application settings. The contribution is a synthesis of how choices in one area constrain or enable decisions in the others. Researchers can use this synthesis to select compatible formulations and design comparable evaluations. VPP operators can use it to assess whether service commitments match resource capabilities and costs, while market designers can examine assumptions affecting participation and delivery. These uses concern method selection and validation

planning; conclusions drawn from numerical studies still require assessment under the intended operating conditions.

The remainder of this review is organized as follows. Section 2 reviews modeling methods for supply-side, energy storage, and demand-side resources within VPPs. Section 3 analyzes coordinated bidding across electricity and coupled energy markets. Section 4 compares uncertainty modeling approaches and scheduling frameworks. Section 5 examines profit allocation mechanisms based on non-cooperative, cooperative, and mixed games. Section 6 reviews distributed optimization and DRL-based scheduling. Section 7 discusses challenges, future research directions, and application examples, and Section 8 concludes the review.

2. Resource Composition, Modeling, and System Architecture

Figure 3 groups VPP resources into supply-side resources, demand-side resources, and energy storage systems (ESSs). A portfolio may contain one category or a combination; a hybrid portfolio is not inherently superior, because its usefulness depends on the intended service and coordination requirements. Sections 2.1–2.3 examine the operating and cost constraints that determine deliverable flexibility. Section 2.4 then connects these models to the commercial and technical interfaces of the VPP.

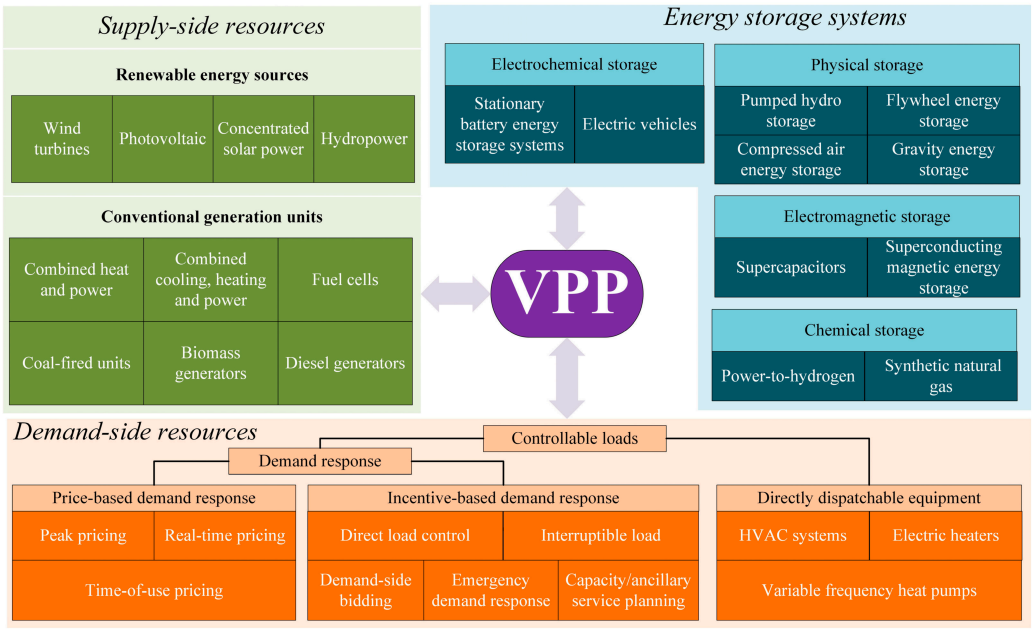


Figure 3. Resource composition of DERs in VPPs.

2.1. Supply-Side Resources

Supply-side resources can be divided into renewable energy sources and conventional generation units. Renewable energy sources include photovoltaics (PV), wind turbines (WT), concentrated solar power, and hydropower, whereas conventional generation units include combined heat and power (CHP), combined cooling, heating, and power, fuel cells [29], coal-fired units, biomass generators [30], gas turbines (GTs), and diesel generators. The modeling of renewable resources generally includes operating cost formulations that capture operation and maintenance costs as well as curtailment costs. For PV and WT, operational constraints typically include curtailment limits and reserve requirements. Concentrated solar power converts solar radiation into thermal energy through photothermal conversion. The thermal energy can then be used for heating, thermal storage, or power generation through heat engines, primarily steam turbines. In addition to the curtailment

and reserve constraints also imposed on PV and WT, concentrated solar power is subject to coupling constraints associated with auxiliary equipment [31–33]. Hydropower utilizes the gravitational potential energy of water, which is converted into kinetic energy through turbines to drive generators. Its operational constraints mainly include output limits and total daily generation limits [34]. For conventional generation units, cost functions are generally classified as linear models [35–37] and higher-order polynomial models, such as quadratic [30,38] and cubic functions [39]. Linear models are often adopted to improve computational efficiency, whereas polynomial models are used to represent actual operating characteristics by fitting unit-specific parameters. Typical operational constraints include unit commitment status, ramping limits, and output bounds [40].

2.2. Energy Storage Systems

ESSs can be classified by storage mechanism into electrochemical, physical, electromagnetic, and chemical storage. Electrochemical storage relies on redox reactions and includes stationary battery ESSs and EVs. Physical storage converts electricity into potential or kinetic energy through technologies such as pumped hydro, flywheels, compressed air, and gravity-based systems. Electromagnetic storage relies on electric or magnetic fields, whereas chemical storage includes power-to-hydrogen and synthetic natural gas. These systems are subject to several common operational constraints, including charging and discharging power limits, mutually exclusive operating states, state-transition constraints, and capacity bounds. Because non-electrochemical storage systems generally have longer service lives than electrochemical storage systems, their operating costs are often represented by annualized equipment costs or equivalent daily costs. Existing studies classify degradation cost models, excluding those that neglect degradation [41], into several categories: simple discharge-only models [42], simplified models that consider both charging and discharging [43–46], cycle-number-based models [47,48], battery-lifespan-based models [29,49,50], and stress-factor models, including simplified [51] and more detailed forms [52].

Battery capacity degradation arises from two mechanisms: cycle aging, which is caused by repeated charging and discharging, and calendar aging, which accumulates over time during idling or light use. The main factors affecting degradation include depth of discharge (DoD), state of charge (SoC), temperature, charging and discharging current magnitude, and timescale. High C-rate operation accelerates degradation. In energy-oriented applications, such as energy arbitrage and day-ahead scheduling, storage duration is usually long, and the actual operating C-rate is typically relatively low [52–54]. Under these conditions, the marginal contribution of current magnitude to additional degradation is smaller than that of DoD, and its effect is coupled with other factors, such as temperature and DoD. In engineering practice, this effect is often simplified or absorbed into other equivalent parameters.

DoD is a critical determinant of cycle aging [53,55]. Deeper discharge is associated with faster degradation, and the relationship is nonlinear [52,53]. Under the same total energy throughput, replacing a limited number of deep cycles with multiple shallow cycles can extend battery life [56]. DoD is defined as the ratio of the change in SoC during each cycle to the rated capacity [52,53]. SoC and temperature affect both cycle aging and calendar aging [52,54,57–59]. High SoC accelerates aging, whereas excessively low SoC can increase impedance and reduce power capability [52,57,58]. Elevated temperatures promote side reactions and degradation, whereas low temperatures may induce lithium plating and impedance growth [52,59]. Thermal management systems are commonly installed in energy storage devices to maintain battery temperature near a reference level. In addition, SoC operating limits in ESSs reduce the effect of SoC on degradation rates. Consequently, the effects of SoC and temperature are often omitted in stress-factor models [52,56]. Time corre-

sponds to calendar aging and reflects capacity fade over time regardless of usage frequency. Although this effect is negligible in short-term assessments involving high-frequency cycling, it becomes significant over multi-year horizons [52,59,60]. Emphasizing DoD enables piecewise linear approximation, thereby supporting fast and stable computation and facilitating integration with economic dispatch and market optimization models. By contrast, explicitly incorporating the nonlinear effects of temperature, SoC, and current magnitude into the cost function substantially increases model complexity and computational burden [56,57,61].

In studies on VPP optimal scheduling, DoD is commonly selected as the primary variable for degradation cost modeling [53,56,57,61]. Average SoC is often adopted, or the effect of SoC is neglected, and a simplified stress-factor model is used. Stress-factor models involving SoC, DoD, and temperature are more suitable for ex post evaluation, typically without explicit treatment of current magnitude. Equivalent full-cycle methods and rainflow counting algorithms can be used to analyze historical power and energy trajectories, after which degradation is accumulated according to the nonlinear dependence on DoD for rapid strategy comparison and cost accounting. More comprehensive models are required in scenarios involving high C-rates, limited thermal management, or prolonged operation at extreme SoC. In such cases, the coupled effects of temperature, SoC, and current magnitude should be explicitly represented to ensure reliability under nonstandard operating conditions [52,54,57–60].

2.3. Demand-Side Resources

Demand-side resources, primarily represented by controllable loads, provide essential system flexibility while requiring lower investment than new power plants or energy storage systems. The costs associated with these resources arise from economic incentives and user discomfort rather than physical degradation. Within VPPs, the modeling of demand-side resources is mainly classified into two categories: the implementation of demand response (DR) strategies and the integration of directly dispatchable equipment.

2.3.1. DR Strategies

The first approach is based on DR strategies, which can be classified into price-based and incentive-based types. Price-based DR includes time-of-use pricing, peak pricing, and real-time pricing. Incentive-based DR includes direct load control, interruptible loads, demand-side bidding, emergency DR, and capacity or ancillary service planning [62]. Price-based DR generally requires extensive experiments to estimate demand price elasticity matrices and is therefore seldom incorporated directly into VPP operational scheduling optimization. Li et al. [43] aggregated transferable loads in a VPP under price-based DR. The scheduling cost was defined as the difference in electricity cost before and after the implementation of time-of-use pricing. The corresponding constraints included load variation rate limits and balance constraints to ensure that the total load remained unchanged before and after the response.

In incentive-based models, user participation is encouraged through incentive cost functions, which are commonly formulated as linear [63], piecewise [64], or quadratic [65] functions. Linear functions are the most widely used. Dong et al. [66] proposed a VPP framework including distributed electric heating devices and EVs, both modeled as curtailable loads. The scheduling costs of these two resources were represented by linear functions, while thermal discomfort costs were not considered. Li et al. [67] aggregated transferable loads and divided them into curtailable and incrementable loads, with linear functions also adopted for the corresponding scheduling costs.

In addition to linear models, piecewise and quadratic functions have also been used. Li et al. [68] aggregated controllable loads from residential, commercial, and industrial

users. For curtailable loads from residential and commercial users, the scheduling cost was modeled using piecewise functions. For residential transferable loads, the scheduling cost was expressed as the difference in electricity cost and was subject to time constraints. Industrial transferable loads were controlled through price-based incentives, and the associated cost was also defined as the difference in electricity cost. In Liu et al. [69], the scheduling cost of curtailable loads was represented by a quadratic function subject to power constraints. Ming et al. [70] also modeled curtailable loads. In that study, incentive factors and load curtailment were linked through piecewise functions, from which a quadratic scheduling cost was derived.

Some studies have adopted more refined load classifications. The VPP framework proposed by Liu et al. [71] included shiftable, transferable, and curtailable loads. Shiftable loads, which are characterized by fixed power and non-interruptible operation, such as washing machines, dishwashers, and dryers, incurred costs defined by the difference in electricity cost and were subject to time and user satisfaction constraints. Transferable loads, which allow adjustment of both power and operating time, such as charging-only EVs, also incurred costs based on electricity cost differences and were subject to power, time, and satisfaction constraints. For curtailable loads, such as air conditioners, linear incentive cost functions were adopted to represent scheduling costs.

The first methodology has limitations in both modeling and practical implementation. From the perspective of consumer psychology [72,73], discomfort increases nonlinearly as the scheduling magnitude increases. This relationship reduces users' willingness to participate and requires higher incentive payments. Simple linear cost functions do not adequately reflect this behavior. Piecewise and quadratic functions provide some improvement, but fixed parameters are often applied across all time periods. As a result, temporal variations in adjustment potential and user baseline demand cannot be captured, and the interests of different parties cannot be properly balanced. Liu et al. [71] further pointed out that these finely classified loads are typically small in scale but large in number. The high costs associated with preliminary agreement signing and subsequent control make such approaches unsuitable for practical application.

2.3.2. Directly Dispatchable Equipment

The second methodology integrates controllable loads, such as electric heaters, variable-frequency heat pumps, and heating, ventilation, and air conditioning (HVAC) systems, into optimization frameworks as directly dispatchable equipment. Scheduling costs are typically modeled by linear functions [74–76], whereas cooling and heating demand is commonly estimated using equivalent thermal parameter models [77–79]. Dong et al. [66] employed equivalent thermal balance constraints to determine the energy consumption of distributed electric heaters, subject to both device power limits and indoor comfort temperature constraints. Zhang et al. [80] incorporated variable-frequency heat pumps in buildings into centralized scheduling. In that study, heating load was calculated using a more detailed equivalent thermal parameter model, in which the four walls and the roof were modeled separately, and predicted mean vote was used to quantify the acceptable indoor comfort temperature range. The relationship between heat pump energy consumption and heating load remained linear at each time step, although the coefficient of performance was modeled as a quadratic function of ambient temperature. Cui et al. [81] aggregated HVAC systems from multiple buildings for hierarchical scheduling, used data-driven methods to simulate dynamic building processes, and considered the thermal storage characteristics of buildings. The HVAC energy consumption model remained linear, with constraints imposed on HVAC power and indoor temperature. Dong et al. [82] aggregated multiple air-conditioning units in residential buildings. The energy consumption of air conditioners was modeled as a

linear function of operating frequency, whereas cooling and heating capacity was represented as a quadratic function of frequency. Both were subject to frequency limits and indoor temperature constraints. The emphasis on building cooling and heating equipment is mainly due to its substantial share of total energy consumption.

The International Energy Agency reported that building operation accounted for approximately 32% of total global energy consumption in 2024 [83]. According to statistics from the United States Energy Information Administration, heating, ventilation, and cooling accounted for approximately 32%, 11%, and 9% of total energy consumption, respectively, in all commercial buildings in 2018, with a combined share of 52% [84]. As a result, such devices have been incorporated into most existing studies on VPP operational scheduling optimization. However, HVAC systems comprise multiple coupled subsystems and exhibit strong nonlinearity and multivariable characteristics [85]. Excessive simplification cannot accurately represent their actual performance and may lead to suboptimal scheduling results. Therefore, directly modeling HVAC systems as simple energy-consuming devices has inherent limitations.

2.4. Commercial Coordination, Technical Control, and Grid Integration

Figure 4 distinguishes commercial coordination, technical control, and the physical network. A VPP coordinates a contracted portfolio of distributed resources through communications, forecasting, scheduling, and market interfaces. The terms VPP and aggregator overlap in the literature [19,86]; neither term alone establishes control authority or the treatment of network constraints. These functions depend on contracts, telemetry, device access, and applicable market rules. The architecture shown here therefore identifies functional roles rather than imposing an absolute distinction between organizational labels.

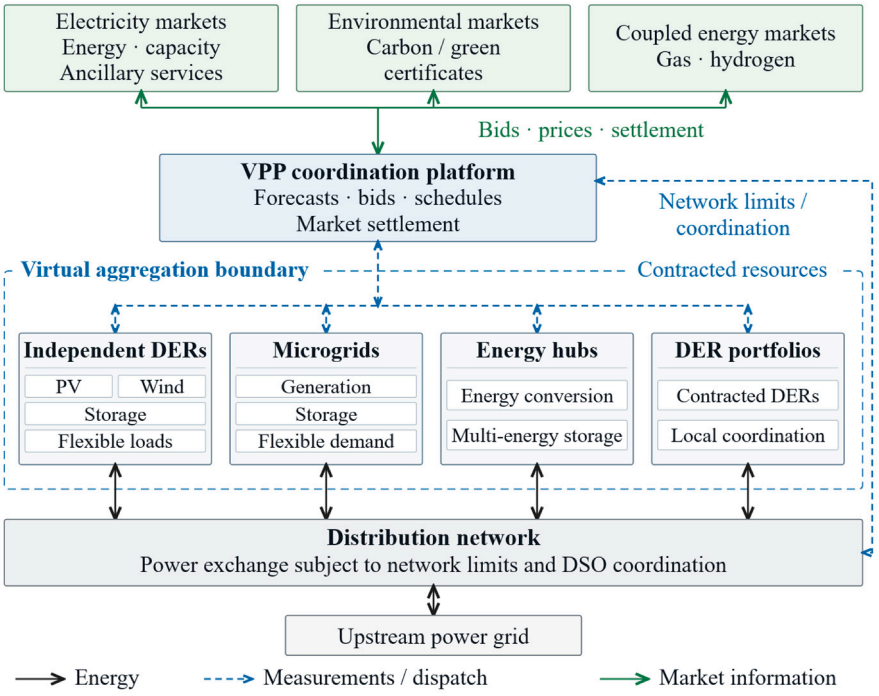


Figure 4. Conceptual integration of a VPP into the power system. Solid black arrows denote physical energy exchange, dashed blue arrows denote measurement and dispatch information, and green links denote market information.

Selected generation, storage, and flexible-load resources exchange power through the existing distribution network. Microgrids, energy hubs, or other aggregated portfolios may participate through an agreed interface, provided that resource ownership and flexibility

are not counted twice. Measurement and availability information support VPP scheduling, while dispatch commands implement the agreed response. Market bids, prices, and settlement information are separate from physical power flows. The distribution system operator (DSO) provides the relevant grid limits and coordination requirements; voltage, thermal, and connection constraints must be represented where they affect deliverability. Thus, VPP integration is a virtual coordination arrangement over existing assets, rather than a new physical grid.

3. Market Participation and Coordinated Bidding

The market decision is which services a physically feasible resource portfolio can commit to, and how the resulting obligations interact. This section considers electricity-market services, carbon and green-certificate arrangements, and coupled gas or hydrogen trading [87–89]. Section 3.1 compares representative market mechanisms; Sections 3.2–3.4 then examine single-service, joint-electricity-market, and coupled-energy strategies.

3.1. Comparative Analysis of Electricity Market Services

Table 1 compares representative market designs through their trading sequence and implications for VPP participation. Previous reviews discuss flexibility, VPP configurations, and regional market design [18,90–92], but similar product names do not establish identical delivery or payment obligations. In United States organized markets, day-ahead positions are followed by real-time balancing. Resource-adequacy mechanisms differ among regions; in particular, ERCOT should be distinguished from markets with explicit capacity remuneration.

Table 1. Selected electricity-market arrangements and their implications for VPP participation.

Market Arrangement	Trading and Operation	Important Distinction	Implication for VPP Models
United States organized markets: PJM Interconnection (PJM) example [93]	Day-ahead energy positions followed by five-minute real-time balancing; ancillary services under product-specific rules.	Resource-adequacy arrangements and product eligibility differ among United States markets.	Represent settlement, qualification, and shared energy/reserve limits; do not transfer all revenue streams between regions.
United States energy-only design: Electric Reliability Council of Texas (ERCOT) [94,95]	Day-ahead financial positions and five-minute real-time energy operation, with ancillary-service arrangements.	ERCOT operates an energy-only wholesale market; the performance credit mechanism should not be treated as an implemented capacity market.	Separate energy and ancillary-service revenues from any assumed resource-adequacy payment.
European exchange trading and transmission system operator (TSO) reserves: Finland example [96,97]	Day-ahead and intraday energy trading through exchanges; reserve procurement and activation through the TSO.	Reserve-availability remuneration differs from activation-energy payments and resource-adequacy capacity remuneration.	Model energy positions, reserved flexibility, activation, and technical prequalification separately.
Australia: National Electricity Market (NEM) [98,99]	Pre-dispatch forecasting followed by five-minute spot-market operation and settlement.	Pre-dispatch forecasts are not financially settled day-ahead energy trades.	Distinguish forecast schedules from binding dispatch and settlement, including service-specific delivery limits.

Table 1. *Cont.*

Market Arrangement	Trading and Operation	Important Distinction	Implication for VPP Models
China: provincial or regional implementation [100]	Medium- and long-term, spot, ancillary-service, and demand-response participation where local rules permit.	Aggregation, eligibility, and available products vary with local implementation.	State jurisdiction, rule version, qualifying resources, and settlement assumptions before comparing returns.

Energy-exchange trading and TSO reserve procurement have distinct roles in Finland. Reserve-capacity payments compensate availability, whereas activation payments concern delivered balancing energy; neither should be conflated with resource-adequacy capacity payments. In Australia's NEM, pre-dispatch is a forecasting process rather than a financially settled day-ahead energy market. In China, registration and locally implemented access requirements determine which services a VPP may offer. The official sources cited in Table 1 support these institutional distinctions.

Consequently, a bidding model cannot be transferred between markets by changing price data alone. Participation qualifications, commitment timing, deviation settlement, and the flexibility reserved for each service must also be represented. The coordination of scheduling and scarcity-related energy/reserve incentives discussed in [101,102] further motivates separating procurement, dispatch updates, and physical delivery. The table is a selective comparison, not an exhaustive product inventory or a guarantee of VPP eligibility.

3.2. Single-Service Bidding Strategy for VPPs in a Single Market

Table 2 compares resource portfolios, market assumptions, service commitments, and solution methods. Single-service formulations isolate a delivery requirement, as in the energy-bidding study involving compressed-air storage [103]. Comparability nevertheless depends on whether technology-specific costs and limits are represented; a generic storage model does not establish the same flexibility as a detailed device model.

Table 2. Comparison of VPP bidding strategies and market participation.

Ref.	Portfolio of DERs	Market Region	Market Types	Market Services	Solution Algorithms
[49]	PVs, ESSs	NEM	Frequency control market	Frequency control ancillary	Nash–Harsanyi bargaining solution
[79]	PVs, HVACs, ESSs, EVs	PJM	Ancillary services market	Regulation	Data-driven, cluster-based methods
[103]	PVs, WTs, conventional generators, ESSs, controllable loads, compressed air energy storage	None	Day-ahead, real-time markets	Energy	MRO
[104]	PVs, centrifugal chiller, ice storage, battery/thermal ESSs, heat pump, combined cooling, heat and power cogeneration unit, multi-energy DRs	China	Peak-regulation market	Peak regulation	Two-stage interval optimization
[105,106]	EVs, ESSs, flexible loads	PJM	Ancillary service market	Frequency regulation	Computation offloading method

Table 2. *Cont.*

Ref.	Portfolio of DERs	Market Region	Market Types	Market Services	Solution Algorithms
[107]	Battery ESS of communication centers	Fingrid	Frequency regulation market	Frequency regulation	Two-stage SP, outer approximation method
[108]	PVs, WTs, ESSs	Iberian	Day-ahead, intraday, balancing markets	Energy	SP
[109]	PVs, WTs, ESSs, DRs	China	Energy, ancillary service markets	Energy, up/down regulation	Multi-objective optimization (linear weighting method)
[48]	PVs, WTs, ESSs, controllable loads	PJM	Energy, ancillary service markets	Energy, frequency regulation	Improved Shapley value method, minimizing deviation algorithm
[110]	PVs, CHPs, battery/thermal ESSs	Italian	Energy, ancillary services markets	Energy, reserve	SP
[111]	PVs, WTs, ESSs, EVs, flexible loads	PJM	Energy, ancillary services markets	Energy, up/down reserve	Non-cooperative game
[112]	PVs, WTs, EVs, ESSs, GTs	China	Energy, ancillary services markets	Energy, up/down frequency regulation	SP method based on conditional value of risk, non-cooperative game
[34]	PVs, WTs, GTs, ESSs, hydropower station	ERCOT	Energy, ancillary services markets	Energy, reserve, up/down regulation	Means of the quantile, superquantile theory
[113]	PV, CHP, gas boiler, heat recovery system, electric chiller, absorption chiller, battery/thermal ESS, thermostatically controlled load	Italian	Capacity, energy, ancillary services, gas markets	Capacity, energy, up/down reserve, gas	RO
[114]	PV, CHP, battery ESS, gas boiler, electrolyzer, absorption chiller, hydrogen vehicle station, daily hydrogen storage, seasonal hydrogen storage	Italian	Capacity, energy, ancillary services markets	Capacity, energy, up/down reserve	Two-stage SP approach with CVaR
[115]	PVs, combined cooling, heating, and power, absorption chillers, battery/thermal ESSs	Egyptian	Energy, thermal energy markets	Energy, thermal energy	Genetic algorithm
[116]	PVs, WTs, GTs, power-to-gas system, flexible loads	China	Forward bilateral contract, real-time power balance, gas markets	Energy, gas	LINGO solver
[117]	PVs, WTs, GTs, battery ESSs, pumped hydro storage systems	China	Energy, carbon trading, green certificate trading markets	Energy, carbon emission quota, green certificate	Multi-objective particle swarm optimization algorithm
[118]	PVs, WTs, GTs, ESSs, DRs	China	Energy, carbon trading markets	Energy, carbon emission quota	Non-cooperative game
[119]	PV, ESS, GTs	China	Energy, carbon trading markets	Energy, carbon emission quota	Non-cooperative game, MRO, ADMM

Table 2. *Cont.*

Ref.	Portfolio of DERs	Market Region	Market Types	Market Services	Solution Algorithms
[120]	PVs, WTs, battery ESSs, thermal power unit	California Independent System Operator/Midcontinent Independent System Operator	Energy, flexible ramp products, carbon trading, green certificate markets	Energy, up/down flexible ramp products, carbon emission quota, green certificate	Two-stage SP, non-cooperative game
[121]	PVs, EVs, battery ESSs	California Independent System Operator	Energy, ancillary services, carbon trading markets	Energy, regulation, carbon emission quota	SP, non-cooperative game
[122]	PVs, WTs, thermal power generators, GTs, carbon capture systems, carbon storage systems, natural gas tank, power-to-gas systems, DRs	China	Energy, gas, carbon trading markets	Energy, gas, carbon emission quota	Improved collaborative evolutionary algorithm
[123]	WTs, GT, ESSs, carbon capture and storage, power-to-gas system, hydrogen storage system, waste heat boiler, gas boiler, multi-energy DRs	PJM	Energy, ancillary services, carbon trading, gas, hydrogen markets	Energy, frequency regulation, carbon emission quota, gas, hydrogen	Primary objective method
[124]	PVs, WTs, waste gasification power plant, carbon capture system, power-to-gas system, hydrogen fuel cells, pressure swing adsorption device, GTs	China	Energy, ancillary services, carbon trading, green certificate trading, hydrogen markets	Energy, frequency regulation, carbon emission quota, gas, hydrogen	Non-cooperative game
[125]	PVs, WTs, thermal power generators, concentrated solar power plant, flexible loads, battery/thermal ESSs	Iberian	Day-ahead, secondary reserve, carbon trading markets	Energy, up/down reserve, carbon emission quota	Two-stage RO

For frequency regulation and peak shaving [49,79,104], read the service and market columns together before comparing solution methods. Regulation requires a portfolio to follow changing dispatch signals; peak-shaving programmes shift or reduce net demand during the relevant intervals. The same installed storage capacity can therefore support different commitments under different power, energy, and response limits. Payment rules and device constraints must be checked together; a more elaborate revenue model or solver alone does not establish higher realizable earnings.

The studies on communication latency and edge coordination [105,106] add a further comparison dimension: timely delivery. Backup-battery aggregation [107] demonstrates an asset-specific implementation rather than a universally transferable portfolio. Read together, the studies support selecting a service only after checking resource feasibility, response timing, and the associated payment and penalty rules.

3.3. Multi-Service Coordinated Bidding for VPPs in a Joint Electricity Market

Participation in individual markets often fails to maximize the revenue of VPPs. Consequently, research has been increasingly directed toward coordinated bidding within multiple electricity markets—including energy, ancillary services, and balancing markets—to

overcome these limitations, as illustrated in Table 2 [34,48,108–112]. The profitability of participation in multi-stage markets was demonstrated by Silva et al. [108], the findings remain constrained by the unique regulatory characteristics of the Iberian mechanism, which may restrict the generalizability of the results to other market regions. The day-ahead bidding problem within the context of energy and reserves was addressed by Fusco et al. [110], although the focus was limited to traditional unit commitment problems due to a simplified VPP structure that failed to exhibit the heterogeneity of DERs. A bi-level collaborative optimization framework for VPP participation in energy and reserve markets was constructed by Du et al. [111] based on the PJM mechanism. While this study provides significant reference value due to the alignment with actual market rules, the modeling of controllable loads requires further improvement.

Joint bidding frameworks for the coordination of energy and frequency regulation are also extensively explored. A framework considering shared energy storage leasing was proposed by Zhang et al. [48], where the primary contribution is found in the realistic frequency regulation revenue model at the real-time stage. However, the day-ahead model requires refinement and the critical issue of time resolution discrepancies between the two stages is ignored. Furthermore, a multi-time bidding framework for VPPs and EV fleets was developed by Qin et al. [112] to provide energy and frequency regulation. A limitation of that study is the treatment of EV fleets as the sole provider of frequency regulation, which neglects the potential of other DER types. To seek more comprehensive coordination, an optimal bidding strategy for VPPs in day-ahead energy, reserve, and frequency regulation markets was proposed by Yang et al. [34] based on the ERCOT mechanism. While the multi-market revenue model offers a reference value, limitations exist due to the neglect of demand-side resource dispatch potential. Because the formulation follows ERCOT-specific participation rules, its conclusions require reassessment before transfer to another market. A resource may support energy delivery and reserve commitments in the same interval, provided that scheduled output, reserved headroom, ramping capability, and any energy-duration limits remain jointly feasible. The same available capability must not be committed more than once.

3.4. Multi-Service Coordinated Bidding for VPPs in the Multi-Energy Coupling Market

Research is committed to the joint participation of VPPs in cross-sector and cross-energy carrier markets to seek broader arbitrage spaces and environmental benefits in response to dual carbon goals and integrated energy system development. This field exhibits significant trends of diversification and complexity, with a structured comparison of these coupling methodologies presented in Table 2.

In terms of power-heat coupling, a scheduling framework within the Egyptian market was developed by Elgamal et al. [115] to emphasize electricity-thermal synergy. It is noted, however, that the genetic algorithm employed may lack efficiency in high-dimensional optimization, and the physical constraints of heat networks are often simplified in such models. Subsequently, regarding power-gas coupling, a dual-energy optimization scheduling model for VPPs within electricity and natural gas markets was proposed by Zhang and Hu [116]. Although enhanced profitability was demonstrated, the reliance on steady-state gas flow analysis potentially overlooks the dynamic pressure constraints and linepack storage effects critical for short-term dispatch.

Furthermore, the coupling of electricity, carbon, and green certificate markets constitutes a significant research trajectory [117–120]. Within these frameworks, various carbon trading modeling approaches are adopted, including single carbon prices with linear scheduling costs [30,117,126–133], tiered/ladder/stepped carbon trading costs [118,120,122,123,134–136], representative or sample day pricing [137,138], and in-

tertemporal carbon trading [125]. In single carbon pricing, carbon trading costs or benefits are calculated annually, and a constant price is assumed. For intertemporal carbon trading, costs are calculated by season or month, with prices varying between these periods. Under representative day pricing, costs are calculated daily, and price fluctuations at different times within the day are considered. A multi-objective optimization framework integrating energy, carbon, and green certificate markets was developed by Guo et al. [117]. While comprehensive, the multi-objective Pareto front often exhibits high sensitivity to weighting factors, and the assumption of perfect liquidity in green certificate markets may deviate from actual low-volume trading conditions. Subsequent studies have refined these mechanisms; for instance, a joint bidding framework based on the tiered model was constructed by Li et al. [118], and this was further extended to non-cooperative game scenarios by Liu et al. [119]. Despite these advancements, the carbon trading and resource cost models remain relatively simplified, often failing to characterize the complex nonlinear coupling between carbon emission intensity and heterogeneous DER output states. Gong et al. [120] developed a bi-level cooperative game framework utilizing game theory. The carbon trading model and resource cost models remain relatively simplified.

Sophisticated research efforts have attempted to establish electricity-gas-carbon-hydrogen coupling frameworks by incorporating low-carbon technologies such as carbon capture, power-to-gas, and hydrogen energy into VPP operations. For instance, VPPs aggregating carbon capture and power-to-gas equipment were integrated into multi-market optimization by Tan et al. [122]. Similarly, hydrogen resources were introduced for multi-objective bidding by Wu et al. [123]. Nevertheless, these models often treat hydrogen as a simplified energy buffer, neglecting the nonlinear efficiency curves of electrolyzers and fuel cells under fluctuating loads. Similar simplifications in carbon trading and DER scheduling models are observed in the work of Jia et al. [124].

Long-timescale coordination, such as participation in capacity markets, remains a critical research gap. A framework encompassing capacity, day-ahead energy, ancillary services, and natural gas markets was proposed by Wang et al. [113]. It is noted, however, that the deterministic approach utilized therein may fail to capture the high uncertainty of capacity calls, potentially leading to significant penalties in real-world market operations. This was extended by Wang et al. [114] through a two-stage scheduling method for multi-energy VPPs with hydrogen integration, realizing synergy between annual planning and daily operations. Yet, the economic viability of the proposed seasonal storage remains a subject of debate given current technological costs and the reliance on idealized long-term climate forecasts.

The comparison in Table 2 indicates that broader market participation should be assessed against the physical flexibility available to support it. For a storage-assisted VPP, energy delivery and regulation commitments draw on shared power and energy limits. Their economic value therefore depends on how capacity is reserved, how deviations are settled, and how degradation costs are represented. Adding market products without preserving these connections can overestimate the portfolio's earning potential. Conversely, a detailed resource model provides limited guidance for bidding if the relevant payment and performance rules are omitted. This contrast can be examined in the detailed service models in [79,105–107,139] and the broader coupled-market formulations in [113,114,122–124]. A useful comparison should therefore ask whether each study represents the constraints that are binding for its intended service and reproduces the corresponding settlement mechanism. Reported profitability should be interpreted together with these assumptions. This provides a more informative basis for assessing a bidding strategy than the number of markets included in its formulation alone.

4. Uncertainty-Aware Scheduling

VPPs operate within a dual stochastic environment characterizing both physical and market systems, exhibiting high dynamics and unpredictability. Deterministic scheduling models are premised on the assumption of perfect forecasting, thereby neglecting the inevitability of prediction errors. This divergence between theory and reality not only causes operating strategies to deviate from optimality but also renders scheduling results infeasible in practice, triggering risks of power imbalances and limit violations. Consequently, internalizing uncertainty into the decision-making framework constitutes a prerequisite for ensuring system safety and economic efficiency. Quantifying the impact of stochastic perturbations on scheduling results via mathematical modeling is therefore critical. Accordingly, this section first dissects the sources of uncertainty in VPP operation, followed by a review of the application status of uncertainty modeling approaches and scheduling frameworks, including SP, RO, distributionally robust optimization (DRO), and multi-time-scale rolling optimization (MRO).

4.1. Sources of Uncertainties

Effective uncertainty management constitutes a pivotal challenge for VPP optimal scheduling. Key uncertainty factors requiring consideration in VPP research are generally classified into two categories: endogenous and exogenous uncertainties [140].

Endogenous uncertainty stems from the stochastic characteristics of internal physical resources within VPPs, encompassing renewable energy generation and loads. Renewable energy uncertainty originates from the inherent intermittency and volatility of wind and solar resources. Wind power uncertainty is attributed to wind speed randomness influenced by geographical and environmental factors. PV generation is determined by solar irradiance, which exhibits distinct seasonal and diurnal patterns while being subject to drastic fluctuations from sudden meteorological changes like cloud cover. Load uncertainty is categorized into rigid (uncontrollable) and flexible (controllable) types based on controllability. Rigid load uncertainty arises from the stochasticity of external drivers. These include heating/cooling demand fluctuations driven by meteorology (e.g., temperature and humidity), behavioral irregularities caused by resident schedules or holiday events, and perturbations introduced by economic activities and measurement noise. Flexible load uncertainty exhibits dual complexity. This category encompasses baseline prediction uncertainty similar to rigid loads, alongside the unobservability of dispatchable potential boundaries (e.g., EV range needs, comfort requirements). Stochasticity also exists in user participation rates and default behaviors. Optimization scheduling models typically integrate renewable energy and rigid load uncertainty into net load uncertainty based on energy balance principles. The response uncertainty of flexible loads necessitates separate treatment as specific stochastic constraints or parameters due to their "dispatchable" resource attributes.

Exogenous uncertainty stems from the external economic market environment beyond the control of VPPs. Market price uncertainty constitutes the primary exogenous challenge for VPPs operating as market participants. Market prices evolve dynamically with factors such as global and regional energy markets, climate, economy, and policies. Price formation is constrained by physical and economic factors, including transmission network constraints, supply-demand elasticity, and generator capacity limits. These factors collectively cause electricity market prices to exhibit volatility far exceeding that of ordinary commodities. Endogenous and exogenous uncertainties coexist in VPP optimization scheduling. Effective modeling of multiple uncertainty factors subject to physical constraints constitutes a core component of VPP uncertainty research.

4.2. SP Methods

SP represents uncertain parameters using probability distributions or weighted scenarios. Its modeling choices concern both the objective, such as expected cost or a tail-risk measure, and the decision structure, such as two-stage recourse. Chance constraints specify acceptable violation probabilities. These choices can be combined within one model; the subsections below distinguish their roles rather than define mutually exclusive methods.

4.2.1. Expectation-Based Models

Expectation-based models rely on risk-neutral assumptions, aiming to minimize the expected value of system operating costs. These models suit day-ahead scheduling scenarios prioritizing long-term average economic benefits over short-term extreme risk sensitivity. The methodology employs Monte Carlo sampling or scenario reduction techniques to generate representative scenario sets from known probability distributions. This process transforms complex scheduling models containing random variables into deterministic mixed-integer programming problems targeting expected costs. An expected value optimization model addressing endogenous uncertainties in load and renewable energy as well as exogenous market prices is constructed by Gholami et al. [141]. DRL is utilized for parameter prediction through training on historical data, and scenario sets are generated to characterize the uncertainty of these predictions. However, the models for distributed energy resources employed in this research are simplified. Fusco et al. [110] constructed probability distribution functions based on historical data, employing scenario trees to simulate PV output and ancillary service demand. K-means clustering extracts typical scenarios to optimize VPP internal resource scheduling. The "generation-clustering" path based on existing historical data appears slightly redundant, despite the method's effectiveness in addressing stochasticity. Furthermore, the model excludes the critical uncertainty factor of price volatility.

4.2.2. Risk-Averse Models

Risk-averse models differ from expectation-based models by focusing on average returns. These models incorporate specific risk metrics, such as conditional value at risk (CVaR), to quantify and mitigate potential economic losses from extreme scenarios or tail probability events. This mechanism enhances system robustness while pursuing economic returns. A risk-averse SP model for VPPs is proposed by Toubeau et al. [142]. Uncertainties in energy prices, reserve prices, load, and output are addressed via scenarios generated to capture extreme conditions. While the representation of the intraday stage is improved, the computational burden increases with the number of scenarios required to cover the uncertainty space. Fluctuations in load, prices, and output are addressed by Ghamarypour and Rahimiyan [143] via a risk-averse strategy. Seasonal time-averages are utilized as inputs in that research, which results in the generation of non-existent scenarios and the omission of extreme conditions. A hybrid SP approach is developed by Xiao et al. [144] to coordinate best-case and worst-case scenarios triggered by exogenous price and endogenous output. This method manages windfall profits, which are not handled by traditional models. DER models are simplified in these studies, and participation is limited to bidding in energy markets.

4.2.3. Chance-Constrained Programming

Chance-constrained programming imposes probabilistic reliability requirements, with solution difficulty depending on the constraint structure and probability model. Some individual constraints admit deterministic linear or conic reformulations under suitable linearity and distributional assumptions. More general cases require approximations or

sampling. Chebyshev- or CVaR-based approximations can be conservative, while sample-based formulations require assessment of sample adequacy and out-of-sample violations. A mixed-integer linear programming (MILP) representation is available only when the underlying algebraic structure permits it.

Chance-constrained programming is further subdivided into individual chance constraints and joint chance constraints. chance constraint defines probabilistic constraints for single physical limits within a power grid, such as the power flow of an individual transmission line. In a study by Aghdam et al. [145], this approach was adopted for the day-ahead scheduling of VPPs to address source-load uncertainty and ensure energy balance at a specified probability level; however, the impact of price volatility was not considered. In contrast, joint chance constraints require that the joint probability of satisfying a set of constraints simultaneously exceeds a minimum threshold, thereby offering more comprehensive protection for system security. A joint chance constraints model for VPPs accounting for source-load uncertainty was proposed by Wang et al. [146], focusing on the collective influence of randomness on multiple constraints, including voltage, current, and power balance. Furthermore, joint chance constraints were utilized by Wei et al. [131] within a leader-follower game model for VPPs and flexible consumers to manage the effects of renewable energy on reserve capacity constraints. In that study, a single-level solution for the model was achieved through approximate transformations and Karush-Kuhn-Tucker (KKT) conditions. It is observed that existing research regarding chance constraints is concentrated on endogenous uncertainties, whereas direct applications to exogenous uncertainties, such as electricity prices, remain limited.

4.2.4. Two-Stage SP

Two-stage SP is utilized to establish long-term strategic decisions in the initial stage, which is followed by the execution of short-term operational adjustments in the subsequent stage to achieve an optimal balance of global expected profit within complex environments. A resource planning method for VPPs that accounts for both endogenous and exogenous uncertainties was proposed by Liang and Ma [147] to optimize the configuration of ESSs and DR resources, although the models of DERs remained simplified and the participation of the VPP in additional markets was not addressed. In a similar approach, a two-stage risk-averse model considering both endogenous and exogenous uncertainties was presented by Li et al. [148], in which the bidding plan of the VPP in the capacity market was confirmed in the first stage and the energy and reserve scheduling plans for detailed DER models were finalized in the second stage, yet the scope of the research did not encompass broader environments such as the carbon trading market. Furthermore, a leader-follower game model for multi-market trading was constructed by Gong et al. [120], where two-stage planning was utilized at the upper level to manage the uncertainty of renewable energy output and a multi-market arbitrage model based on deterministic prices was established at the lower level. However, the reliability of the model is limited by the neglect of concurrent load and price volatility, which necessitates further development to address multi-source uncertainties effectively.

Table 3 separates objective choice, reliability requirements, and recourse structure. Expected-cost models emphasize average performance, whereas risk measures make exposure to adverse outcomes explicit. Chance constraints require a stated probability model and violation tolerance; two-stage formulations distinguish commitments from later corrective actions. Selecting among these choices requires representative data and a consistent evaluation of expected cost, tail losses, violations, and solve time. Scenario reduction can improve tractability but may omit rare events, so it should be assessed against the risk measure used.

Table 3. Comparison of SP methods for VPPs.

Method Type	Core Concept	Advantages	Disadvantages	Scenarios
Expectation-based models	This approach minimizes the expected value of operating costs based on known probability distributions of uncertain parameters.	Supports expected-cost planning for risk-neutral decisions.	Expected-cost objectives do not explicitly control tail losses.	Both endogenous and exogenous uncertainties
Risk-averse models	Uses risk metrics such as CVaR to manage tail losses.	It enhances the robustness of the system against economic losses triggered by extreme probability events.	Greater risk aversion may reduce expected economic returns.	Both endogenous and exogenous uncertainties
Chance-constrained programming	This formulation requires that physical constraints are satisfied at a predefined confidence level to manage operational reliability.	Balances reliability and cost through probabilistic violation limits.	May be nonconvex; approximations can yield conservative schedules.	Endogenous uncertainties
Two-stage SP	This framework bifurcates the problem into a first-stage proactive decision and a second-stage reactive recourse decision.	It aligns the decision-making process with the chronological sequence of day-ahead and real-time operations.	More scenarios increase model size and usually computational burden.	Both endogenous and exogenous uncertainties

4.3. RO Methods

RO methods characterize parameter fluctuations through the construction of an uncertainty set to pursue optimal decisions under the worst-case scenario. Based on decision timing and mathematical structures, research is categorized into single-stage RO and multi-stage RO.

In the field of single-stage RO, different paths for conservatism regulation are provided by Hadi Nemati in References [149–151]. A model is constructed in [149] for the bidding of a Renewable-only VPP in energy, reserve, and balancing markets. Uncertainties regarding day-ahead and reserve prices, imbalance prices, non-dispatchable renewable output, and load are incorporated. Flexible regulation of dispatch conservatism is achieved by setting a mathematical threshold of average regret as a hard boundary to limit the coverage of the uncertainty set over extreme profit loss scenarios. In [150], optimization strategies for VPPs in day-ahead, secondary reserve, and sequential intraday markets are explored. Uncertainties including market prices, renewable output, and flexible load are addressed. Positive and negative deviations of variables are characterized by asymmetric uncertainty sets, with the total number of periods deviating from predicted values restricted by an uncertainty budget parameter. In the mathematical formulations of [149,150], profit losses from price fluctuations and volume fluctuations are treated as sums of independent linear deviations, without explicit modeling of the product terms arising from the multiplication of price and volume. The mathematical structure of single-stage RO is further improved in [151]. Bilinear terms arising from the multiplication of price and volume fluctuations in the revenue function are no longer avoided when addressing uncertainties in day-ahead

energy prices, reserve prices, renewable output, and flexible load. A nonlinear objective function containing products of uncertain variables is converted into equivalent linear constraints via dual transformation and the Big-M method. Consequently, a flexible worst-case profit under the coupling of price and volume is determined within a single-level MILP framework, eliminating evaluation bias caused by the assumption of independent variables.

Adaptive RO allows recourse decisions to respond to revealed uncertainty. Two-stage formulations are commonly expressed as min–max–min problems, while more general multistage formulations involve additional information stages. Adaptivity can reduce conservatism relative to static decisions, subject to the chosen recourse representation. However, complex non-convex products caused by the simultaneous introduction of price uncertainty and decision variables like bid volumes lead to simplifications in modeling. A two-stage robust bidding model for multi-energy VPPs is developed in [140], where only endogenous uncertainties such as renewable output and multiple loads are considered. Similarly, in [152], a three-level adaptive structure is utilized to simulate recourse capability for VPP scheduling involving power-to-hydrogen, yet uncertainty modeling remains limited to renewable output and load, excluding market prices from the robust framework.

Further exploration of multi-source uncertainties involving both prices and physical quantities has been conducted. A time-of-use price uncertainty set is constructed in [153] using 1-norm and infinity-norm constraints to address fluctuations in prices, renewable output, and load. A two-stage adaptive solution is realized via the column and constraint generation algorithm (C&CG). A two-stage interval RO model is established in [154], employing a hybrid strategy of C&CG s to optimize multi-source uncertainties including prices, EV quantities, and PV output. In [155], a data-driven scenario RO method is proposed for distribution-side VPPs involving vehicle-to-grid resources. Price parameters are instantiated through scenarios generated from historical data, while a robust set is constructed for load. Dispatch risks are reduced in the second stage through adaptive charging and discharging plans.

Additionally, a stochastic-robust hybrid modeling strategy is adopted in some studies. Price uncertainty is handled via stochastic scenario programming in [156], while RO modeling is retained for renewable output and load fluctuations, with solutions obtained using KKT conditions and the C&CG. In [157], an improved two-stage stochastic optimization model is developed. Uncertainties in prices, WT output, and reserve load are processed using an improved Benders decomposition algorithm. The advantages of the hybrid method in balancing adaptability and economy are highlighted through comparison with traditional RO.

Table 4 contrasts static decisions, adaptive recourse, and stochastic–robust combinations. The practical choice concerns which decisions can change after information arrives and how the uncertainty set is calibrated. Recourse may reduce conservatism, but it introduces additional variables and solution effort. Hybrid formulations can assign different representations to resource and price uncertainty, without automatically resolving nonlinear coupling. Comparisons should report out-of-sample delivery and cost together with computational effort under the same physical and market assumptions.

Table 4. Comparison of RO methods for VPPs.

Method Type	Core Concept	Advantages	Disadvantages	Scenarios
Single-stage RO	Regulating uncertainty set boundaries within a single-level framework using parameters like average regret threshold or asymmetric budget	Can be efficient when price–power terms admit suitable linearization	Static decisions lacking dynamic mapping between variables and uncertainty realizations	Both endogenous and exogenous uncertainties
Multi-stage adaptive RO	Adapts later-stage decisions to revealed uncertainty; nested formulations may be used	Can reduce conservatism through recourse aligned with the decision sequence	Recourse and uncertainty coupling can create nonconvexity and high solution costs	Resource and/or market uncertainty, depending on the formulation
Stochastic-robust hybrid method	Modeling exogenous prices with probabilistic scenarios and covering endogenous fluctuations with robust sets	Effective balance between economy and robustness while avoiding non-convex bottlenecks from price-power products	Depends on price-scenario quality; more scenarios enlarge the model	Both endogenous and exogenous uncertainties

4.4. DRO Methods

DRO represents uncertainty about the probability distribution through an ambiguity set of candidate distributions. The objective commonly optimizes worst-case expected cost or profit over this set; distributionally robust chance constraints instead limit violation probabilities across its members. Moment information and statistical distances are alternative tools for constructing an ambiguity set and can be used with chance constraints. The following categories therefore describe complementary formulation choices rather than an exclusive partition.

4.4.1. Moment-Based DRO

Moment-based DRO uses statistical information when a single probability distribution cannot be specified reliably. First- and second-order moment information defines a set of admissible distributions. Under suitable assumptions, dual reformulations lead to second-order cone or semidefinite programs; mixed-integer recourse and nonlinear constraints can substantially increase solution effort. Babaei et al. [158] represent the temporal correlation of virtual net load using empirical mean and covariance information and formulate a mixed-integer conic model for flexibility assessment. Feng et al. [159] use moment information in a more complex scheduling model with mixed-integer recourse and develop an improved nested C&CG algorithm. These examples show that the moment description and the recourse structure jointly determine computational requirements; moment information alone does not guarantee tractability.

4.4.2. Statistical Distance-Based DRO

DRO methods based on statistical distances utilize the principles of non-parametric estimation to construct ambiguity sets centered on the empirical distribution by defining statistical distances between probability distributions. Although various metrics for statistical distance are available, including the Wasserstein distance [160] and the Kullback–Leibler divergence [161], the Wasserstein distance has emerged as the predominant choice in contemporary power system optimization research. This preference is attributed to

the capability of the Wasserstein distance to capture the geometric structure of probability distributions and its favorable convergence characteristics on discrete support sets. The aforementioned Wasserstein metric was employed by Song et al. [162] to model the fluctuations of renewable energy. In that study, affine decision rules were introduced to approximate infinite-dimensional problems as MILP formulations, thereby achieving an equilibrium between theoretical rigor and computational feasibility in the transactive control of thermostatically controlled loads. A similar methodology was adopted by Esfahani et al. [163], in which prediction errors of uncontrollable loads were described using Wasserstein balls. The KKT conditions were subsequently utilized to resolve a bi-level game problem concerning the construction of VPPs. However, despite the theoretical dominance of Wasserstein-based methods, substantial computational burdens are often induced by their continuous nature. Consequently, for large-scale and complex data scenarios, another branch of research has begun to explore norm-constrained methods based on discrete scenarios, which are considered a discretized implementation of statistical distances. For instance, 1-norm and infinity-norm constraints were utilized by Xiong et al. [164] to construct ambiguity sets for multi-energy complementary systems involving wind, solar, and thermal energy. Such discretization allows the model to be seamlessly integrated with advanced decomposition algorithms, such as the adaptive buffer-C&CG method, which significantly enhances the solution speed of multi-region coordination. The divergence between these two research paths reflects a fundamental trade-off between the pursuit of theoretical rigor, represented by Wasserstein-based methods, and the pursuit of large-scale computational efficiency, represented by discrete norm-based methods.

4.4.3. Distributionally Robust Chance-Constrained Optimization

Distributionally robust chance constraints are useful when the model must bound the probability of events such as voltage excursions, line overloads, or delivery shortfalls. The ambiguity set identifies the distributions against which this requirement is tested; its construction may use moments, statistical distances, or other justified distributional information. The reliability requirement and the ambiguity-set construction therefore address different modeling choices. Individual chance constraints control the risk of each specified limit, whereas a joint chance constraint controls the probability that at least one of a specified set of limits is violated. These guarantees depend on the ambiguity set, calibration assumptions, and system representation.

In research regarding distributionally robust individual chance-constrained modeling, uncertainties in market prices and WT output are addressed by Liu et al. [165]. A Wasserstein distance is utilized to construct the ambiguity set, and the CVaR of bidding revenues for VPPs, along with the physical boundary constraints of static operating envelopes, is managed through individual chance constraints. Bilinear terms in the revenue function, arising from the coupling of prices and WT output, are handled via decision decoupling and affine approximation techniques. In scenarios involving multiple VPPs, power deviations in electricity-heat multi-energy flows are addressed by Wen et al. [166] through a two-stage trading model incorporating carbon quotas for EVs. Real-time electricity and heat energy balance constraints, as well as carbon emission quota compliance constraints, are processed using individual chance constraints. The output fluctuations of heterogeneous distributed resources and the dynamic variations in line thermal limits influenced by the environment are focused on by Chen et al. [167]. Boundary constraints for the feasible operating region of the aggregated power output of the VPP are defined, and the exogenous influence of the environment is addressed through dynamic line rating technology. Among these studies, the simultaneous treatment of endogenous and exogenous uncertainties is achieved only by Liu et al. [165], resulting in a high degree of economic integrity in the decision model.

Although carbon quotas or dynamic line rating are introduced by Wen et al. [166] and Chen et al. [167], the modeling is focused on the local balance of power fluctuations, without considering price uncertainty.

Regarding distributionally robust joint chance-constrained research, the recovery of three-phase unbalanced distribution networks is targeted by Mohy-ud-din et al. [168]. To manage deviations in renewable energy output and load forecasting, VPP flexibility is quantified using a hierarchical framework. Probabilistic control is implemented through joint chance constraints over the power output limits of distributed generators and ESSs, network-wide node voltage ranges, branch flow limits, and current imbalance constraints. Under a transmission-distribution coordinated architecture, the flexibility demand constraints of the transmission system are guaranteed by Cai et al. [169] using joint chance constraints to address renewable energy and load forecasting errors, thereby preventing physical violations triggered by the large-scale invocation of regulation resources. A distributionally robust joint chance-constrained optimization framework is constructed by Onsomu et al. [170] to address uncertainties in PV and WT output. System power balance constraints and spinning reserve capacity adequacy constraints are handled through the combined use of heuristic algorithms and binomial expansion techniques. A high depth of physical system simulation is provided in these studies, where the coupling characteristics of endogenous uncertainty across multi-dimensional physical spaces are captured through joint probability descriptions to ensure system safety. However, the modeling of price fluctuations is not involved in these studies, and the decision logic remains confined to the steady operation of the physical layer, lacking completeness in addressing economic risks within a power trading environment.

Table 5 compares the information used to build ambiguity sets and the risks controlled by the resulting models. Moment-based sets retain selected statistics, distance-based sets describe departures from an empirical distribution, and distributionally robust chance constraints specify reliability requirements. A set does not automatically contain the true distribution, and statistical guarantees depend on calibration, data assumptions, and the chosen reformulation. Mixed-integer or nonlinear device and network constraints can add substantial solution effort. Consequently, ambiguity-set sensitivity, out-of-sample violations and costs, and computation time should be reported together.

Table 5. Comparison of DRO methods for VPPs.

Method Type	Core Concept	Advantages	Disadvantages	Scenarios
Moment-based DRO	Constructing ambiguity sets via first- and second-order statistics for second-order cone programming or semi-definite programming reformulations	Represents covariance; suitable convex formulations permit tractable reformulation	High sensitivity to discrete decision variables and non-convex hierarchical model structures	Resource and/or market uncertainty, depending on the formulation
Statistical distance-based DRO	Utilizing Wasserstein metric or norms to quantify the discrepancy between empirical and true probability distributions	Can provide out-of-sample guarantees under appropriate assumptions and calibration	Continuous-support formulations can be large; approximations may reduce accuracy	Resource and/or market uncertainty, depending on the formulation
Distributionally robust chance-constrained	Imposing probability violation upper bounds on physical constraints via individual or joint confidence levels	Controls violation risk and can represent coupled network constraints	Mathematical complexity in joint formulations and conservatism in CVaR approximations	Mainly endogenous; rarely both

4.5. MRO Methods

MRO is utilized as another effective methodology for the operational optimization and scheduling of VPPs while accounting for both endogenous and exogenous uncertainties. The fundamental principle of this approach involves exploiting the variations in prediction accuracy across different time scales. Through a mechanism comprising day-ahead global planning and intraday or real-time rolling correction, the impact of uncertainty on the operation of the system is progressively mitigated as time progresses. Specifically, global plans are formulated during long time scales, such as the day-ahead stage, through the application of short-term forecasts. Conversely, during short time scales, including intraday or real-time stages, updated ultra-short-term forecasts or real-time measurement data are employed. A rolling horizon strategy is adopted to dynamically adjust day-ahead plans, thereby minimizing the risk of system mismatch induced by endogenous and exogenous uncertainties while ensuring that physical constraints are satisfied.

During the adjustment phase of short time scales, differentiated cost functions are designed in various studies based on the specific types of services involved. For applications centered on energy market arbitrage and deviation settlement, objective functions are primarily focused on economic indicators to address price fluctuations. For instance, Pandey et al. [171] formulated a multi-objective framework to maximize net profit while minimizing pollutant emissions for multi-regional VPPs, facilitating optimal resource scheduling across both hourly and real-time scales. A comprehensive objective function was constructed by Mei et al. [172], which incorporates real-time deviation penalty costs and ESS degradation costs. In this research, asymmetric penalty prices for positive and negative deviations were distinguished through the introduction of state variables. Furthermore, rolling optimization was utilized to dynamically adjust the charging and discharging of energy storage to approximate day-ahead plans, thereby mitigating the impact of renewable energy output deviations on economic efficiency. Similar economic-oriented strategies were adopted by Chang and Yang [129] and Du et al. [173]. In the former study, real-time corrections of carbon trading costs were explicitly included in the real-time re-dispatch cost function. In the latter study, equipment operational adjustment costs and external transaction default costs were integrated during the real-time operation stage to manage dual fluctuations in prices and loads within multi-energy coupling systems involving electricity and hydrogen. Conversely, when VPPs participate in auxiliary services such as frequency regulation, the focus of the cost functions shifts from economic performance to physical performance indicators to primarily address endogenous power fluctuations. The real-time control layer developed by Liu et al. [174] is designed to minimize the violation of tracking for dynamic regulation signals from the power grid. The objective function in that work was defined as the integral of the absolute error between the actual power response and the signals issued by the independent system operator (ISO). This approach reflects a prioritization of the precision of grid frequency support.

The quality of decisions in MRO is highly dependent on the sources of short-term data and the evolution of forecasting technologies. A transition from traditional statistical models toward high-dimensional hybrid deep learning models is demonstrated in existing literature, encompassing diverse predictions for endogenous resource output and exogenous market signals. Traditionally, rolling optimization has relied predominantly on fundamental statistical methods or real-time measurements. In the real-time model predictive control framework developed by Liu et al. [174], an autoregressive moving average model was utilized to perform short-term extrapolation forecasts for PV output and dynamic regulation signals. These forecasts served as inputs to optimize the real-time setpoints for distributed power sources and ESSs. The granularity and categories of data were explicitly distinguished by Du et al. [173]. In the intraday stage of that study, ultra-short-term prediction data were

utilized, covering WT output, PV output, electrical load, and hydrogen load. In the real-time stage, five-minute real-time measurement data were directly applied for rapid corrections. In contrast, a more advanced data-driven approach was represented by Kim and Kim [175], in which a hybrid decomposition-based deep learning forecasting framework was proposed. Within a real-time rolling window occurring every fifteen minutes, non-stationary net load sequences were predicted through high- and low-frequency decoupling via a hybrid decomposition model. This high-precision prediction-correction mechanism significantly mitigated the risk of real-time power mismatch induced by prediction errors in endogenous sources and loads.

To overcome the inherent limitations of deterministic rolling optimization when addressing unavoidable deviations between predicted and measured data, various integrations of rolling optimization with alternative uncertainty-handling methodologies have been explored in recent research. For instance, a rolling-horizon SP framework was developed by Yi et al. [176] for the real-time scheduling of shiftable loads. Within this framework, an SP problem encompassing multiple scenarios is solved in each rolling window, which enables decisions to adapt effectively to the stochastic evolution of future load. Furthermore, risk control was emphasized in the study by Mei et al. [172]. Although CVaR is primarily introduced during the day-ahead stage to quantify risks associated with prediction errors, the resulting risk-averse reserve capacity is transferred as a rigid parameter to the real-time rolling model. Consequently, an effective coupling of long-term risk assessment and short-term rolling control is achieved. Similarly, a two-stage optimization framework was constructed by Qin et al. [112], in which complex risk-averse models are utilized in the day-ahead stage to generate multi-scenario scheduling plans, while subsequent attempts are made to rectify deviations across scenarios during the real-time phase. However, a common challenge is shared by these multi-scenario or multi-stage methodologies. Specifically, significant redundancy of computational resources is incurred, and the engineering difficulty of identifying a unique execution trajectory from a multitude of stochastic scenarios during the real-time stage remains unresolved.

MRO can embed SP, RO, DRO, or chance constraints; Du et al. [173], for example, combine rolling updates with probabilistic power-balance requirements. This compatibility does not remove uncertainty between updates or make nested models automatically suitable for fast dispatch. Forecast quality, window length, data availability, and the time allowed for each solve jointly determine applicability. The uncertainty model and the updating frequency should therefore be selected and evaluated together.

Table 6 should be read across three dimensions: uncertainty coverage, market commitments, and the scheduling framework. A check mark records that a factor is represented; it does not establish calibrated risk protection or better performance. For method selection, first identify the uncertain quantities and binding service obligations, then check how information and recourse are represented. The number of markets or uncertainty sources included is not, by itself, a quality ranking.

Tables 3–6 can be used as a sequence of design checks for a VPP making day-ahead commitments with later corrective dispatch. First, identify the uncertain quantities affecting delivery or settlement and the available observations. Representative scenarios and credible probabilities can motivate SP; credible operating ranges can motivate RO; uncertainty about the distribution can motivate DRO. These choices require calibrated scenarios or sets and do not form a quality ranking. Next, specify which decisions precede information and which can adapt. MRO can update these formulations as information arrives, subject to the dispatch deadline. Finally, compare feasible net returns, delivery violations, and solution time under the same portfolio and market rules.

Table 6. Comparative analysis of related works.

Ref.	Endogenous Uncertainties			Exogenous Uncertainties		Electricity Markets			Other Markets	Methods
	Renewable Energy	Loads	Control-lable Loads	Energy Price	Reserve Price	Capacity Market	Energy Market	Ancillary Service Market		
[110, 142]	√	√	×	√	√		√	√	×	SP
[120]	√	×	×	×	×	×	√	×	Carbon + Green	SP
[114]	√	√	×	√	√	√	√	√	×	SP
[141,143, 144,177]	√	√	×	√	×	×	√	×	×	SP
[145, 146]	√	√	×	×	×	×	√	×	×	SP
[131]	√	×	×	×	×	×	√	√	Carbon	SP
[178]	√	×	×	√	×	×	√	×	×	SP
[148]	√	√	√	√	√	√	√	√	×	SP
[147]	√	√	√	√	×	×	√	×	×	SP
[140]	√	√	×	×	×	×	√	×	Gas + Carbon	RO
[153]	√	×	Tariff + EV	×	×	×	√	×	×	RO
[154]	√	×	EV	×	×	×	√	×	×	RO
[155]	×	√	×	√	×	×	√	×	×	RO
[156]	√	√	×	√	×	×	√	×	×	RO
[157]	√	√	×	√	√	×	√	√	×	RO
[130]	√	√	×	×	×	×	√	×	×	RO
[154]	√	√	EV	√	×	×	√	×	×	S + RO
[156]	√	√	×	√	×	×	√	×	×	S + RO
[179]	√	×	×	√	√	×	√	√	×	S + RO
[158,159, 166]	√	√	×	×	×	×	√	×	×	DRO
[162, 164]	√	×	×	×	×	×	√	×	×	DRO
[163]	×	√	×	×	×	×	√	×	×	DRO
[166]	√	√	×	×	×	×	√	×	Carbon	DRO
[165]	√	×	×	√	×	×	√	×	×	S + DRO
[48,174]	√	×	×	×	×	×	√	√	×	MRO
[173]	√	√	×	×	×	×	×	×	Carbon	MRO
[175,176, 180]	√	√	×	√	×	×	√	×	×	MRO
[112]	√	×	×	√	×	×	√	√	×	S + MRO
[172]	√	×	×	√	×	×	√	×	Carbon	S + MRO
[129]	√	√	×	√	×	×	√	×	Carbon + Gas	S + MRO

Note: √ indicates that a factor is considered; × indicates that it is not.

5. Game-Theoretic Coordination and Benefit Allocation

Participant coordination raises two linked questions: who controls prices and operating decisions, and how the resulting cooperative surplus is shared. Table 7 compares competitive, cooperative, and mixed game formulations through these roles. Non-cooperative models describe strategic responses; allocation rules distribute a specified coalition value. Neither task alone establishes a stable and implementable agreement. The relevant choice depends on decision rights, outside options, information exchange, and the operating costs included in the surplus.

Table 7. Technical comparison of game methods for VPPs.

Method	Object	Stability & Incentive	Budget Balance	Complexity	Application Focus
Stackelberg game	Individual net benefits	Strategic equilibrium via optimal response.	Not applicable	Moderate	Hierarchical control and market bidding.
Shapley value	Incremental profits	Axiomatic fairness based on marginality.	Fully satisfied	High	Fair profit sharing for heterogeneous resources.
Nucleolus	Shared costs/surplus	Minimizes coalition dissatisfaction; lies in the core when the core is nonempty.	Fully satisfied	Very high	Robust long-term cost-sharing projects.
Nash bargaining	Utility increments	Pareto optimality via mutual compromise.	Fully satisfied	Varies.	Peer-to-peer trading and privacy sharing.
Mixed game	Hierarchical revenues	Depends on equilibrium and allocation assumptions.	Internally satisfied	High	Multi-entity collaborative scheduling.

Table 7 separates authority over operating decisions from the rule for sharing surplus. The leadership and pricing columns in Table 8 show who commits first and who responds. These roles should be established before selecting a game model, with coalition values calculated from consistent dispatch and cost assumptions. A Shapley allocation rewards marginal contributions but need not lie in the core; the nucleolus addresses coalition dissatisfaction over a specified feasible set, and bargaining depends on disagreement payoffs. Budget balance alone therefore does not show that participants will remain in the coalition.

Table 8. Comparative analysis of works based on non-cooperative games.

Ref.	Uncertainties & Handling Methods	Leader-Follower	Services Priced by the Leader	Portfolio of DERs (Leader)	Portfolio of DERs (Follower)	Objectives of Upper/Lower Levels	Solution Algorithms
[181]	None	DSO-VPPs	Energy, up/down reserves	PVs, WTs, DGs, EV loads, ESSs	PVs, WTs, DGs, EV loads, shiftable loads, curtailable loads	Minimization of DSO operating costs/Maximization of VPP net profit	KKT + Strong duality
[182]	None	DSO-VPPs	Energy, up/down reserves	PVs, WTs, DGs	PVs, WTs, DGs, EV loads, shiftable loads, curtailable loads	Minimization of DSO operating costs/Maximization of VPP net profit	KKT + Strong duality

Table 8. *Cont.*

Ref.	Uncertainties & Handling Methods	Leader-Follower	Services Priced by the Leader	Portfolio of DERs (Leader)	Portfolio of DERs (Follower)	Objectives of Upper/Lower Levels	Solution Algorithms
[183]	None	DSO-VPPs	Energy, up/down reserves	PVs, WTs, DGs	PVs, WTs, DGs, shiftable loads, EV loads	Minimization of DSO operating costs/Maximization of VPP net profit	KKT + Strong duality
[184]	None	DSO-VPPs	Energy, up/down reserves	PVs, WTs, DGs	PVs, WTs, DGs, EVs, ESSs, two types of curtailable loads	Minimization of DSO operating costs/Maximization of VPP net profit	KKT + Strong duality
[185]	PVs, EV loads & RO	DSO-VPPs	Energy, up/down reserves	None	PVs, DGs, ESSs, EV loads, curtailable loads	Minimization of DSO operating costs/Maximization of VPP net profit	KKT + Strong duality
[186]	PVs, WTs & Individual chance constraints	ISO-VPPs	Energy	DGs	PVs, WTs, DGs, ESSs	Minimization of risk-adjusted ISO operating costs/Maximization of risk-adjusted VPP net profit	Genetic algorithm
[77]	None	VPPs-ISO	Energy	PVs, DGs, EVs, HVAC	None	Maximization of VPP net profit/Minimization of ISO dispatch costs	KKT + Strong duality
[111]	PVs, WTs, load & Joint chance constraints	VPPs-ISO	Energy, up/down reserves	PVs, WTs, ESSs, curtailable loads, shiftable loads	DGs	Maximization of VPP net profit/Minimization of ISO operating costs	KKT + Strong duality
[187]	WTs, load, price & Risk-averse methods	VPPs-ISO	Energy	WTs, ESSs, interruptible loads	None	Maximization of the risk-adjusted difference between day-ahead VPP net revenue and real-time imbalance costs/Minimization of ISO operating costs	KKT + Strong duality
[188]	PVs, WTs, price & SP + RO	VPP-DR aggregators	Energy	PVs, WTs, GT, ESSs, power-to-gas unit, gas storage system, DR aggregators	DR aggregators	Maximization of VPP expected net profit/Maximization of the net utility of each DR aggregator	KKT + Strong duality + C&CG
[189]	PVs, WTs & Risk-averse methods	VPP-EVs	Energy	PVs, WTs, ESSs, EV loads	EVs	Maximization of risk-adjusted VPP net profit/Minimization of the difference between charging costs and satisfaction levels	KKT + Strong duality

Table 8. *Cont.*

Ref.	Uncertainties & Handling Methods	Leader-Follower	Services Priced by the Leader	Portfolio of DERs (Leader)	Portfolio of DERs (Follower)	Objectives of Upper/Lower Levels	Solution Algorithms
[190]	PVs, WTs, price & Risk-averse methods	VPP-each DER	Energy	PVs, WTs, DGs, ESSs, controllable load	Each DER	Maximization of risk-adjusted VPP net profit/Minimization of the operating costs of each DER	KKT + Strong duality
[191]	PVs, WTs & Individual chance constraints	DER agent-VPP	Energy	None	PVs, WTs, DGs, DR, ESSs	Maximization of DER agent net profit/Minimization of VPP operating costs	KKT + C&CG + Pareto-optimal equilibrium point
[44]	PVs, WTs, load, price & Risk-averse methods	VPP-DER agent	Energy	None	PVs, WTs, DGs, ESSs, EVs, interruptible loads, shiftable loads, residential loads	Maximization of risk-adjusted VPP net profit/Minimization of DER agent operating costs	Bisection method
[192]	None	VPP-DER aggregators	Energy	None	Energy supply aggregator, residential load aggregator, EVs aggregator, carbon treatment system aggregator	Maximization of VPP net profit/Minimization of the operating costs of each DR aggregator	Hybrid nutcracker optimization algorithm + Quadratic programming method
[193]	None	VPP-ESSs & Consumers	Energy	PVs, WTs, GTs	ESSs, consumers	Maximization of VPP net profit; Maximization of ESS net profit/Minimization of consumer energy costs	Nondominated sorting genetic algorithm II

5.1. Non-Cooperative Game

Non-cooperative games describe strategic interactions among self-interested participants. Stackelberg games are one hierarchical form: a leader commits to a decision, and followers respond by optimizing their own objectives. Their suitability depends on whether the modeled timing and authority match the application. The following subsections distinguish external interactions with system operators from internal interactions between VPP operators and resource owners.

5.1.1. Leader-Follower Games Between VPPs and Grid Operators

A review of external interaction mechanisms for VPPs under varying game-theoretic leadership structures is presented in this section. Existing literature, predominantly grounded in Stackelberg game theory, categorizes frameworks into two distinct architectures based on decision-making hierarchies: distribution system operator (DSO) or ISO-led configurations, and VPP-led configurations.

Within frameworks characterized by DSO or ISO leadership, fundamental deterministic bi-level programming models were constructed by Ebrahimi et al. [181], Yi et al. [182],

Zhang et al. [183], and Li et al. [184]. A unifying feature of these studies is the application of KKT conditions combined with strong duality theory to convert bi-level problems into single-level MILP formulations. Conversely, distinctions arise regarding the heterogeneity of internal resources within the follower VPPs and the associated model complexity. These range from singular traditional distributed generators (DGs) to intricate aggregations comprising EVs, ESSs, and diverse controllable loads. To address the limitations inherent in deterministic models, RO was integrated into this framework by Lin et al. [185] to mitigate the volatility associated with PV outputs and EV loads. In contrast to the aforementioned approaches based on mathematical programming, separate chance constraints were employed by Zhang et al. [186] within an ISO-led game to address the stochastic nature of renewable energy. Furthermore, a genetic algorithm was utilized to derive optimal system dispatch solutions while accounting for risk costs.

Conversely, the decision-making logic is inverted when the VPP assumes the dominant position in the game by leveraging its aggregation scale. The mechanisms by which a VPP guides a lower-level ISO to minimize dispatch costs within a deterministic environment were investigated by Pourghaderi et al. [77]. To enhance strategic adaptability in complex environments, a bi-level model incorporating joint chance constraints was proposed by Du et al. [111]. This model aims to maximize the net profit of VPPs by coordinating the multiple uncertainties associated with PVs, WTs, and loads. Building upon this foundation, emphasis was placed on risk management by Kardakos et al. [187], where risk-averse methodologies were introduced to quantify the impact of WT output and market price fluctuations on revenues in both day-ahead and real-time markets.

Table 8 compares leadership, pricing authority, service scope, resource portfolios, and solution methods. These dimensions should be read together: a leader–follower structure defines timing, while an equilibrium claim requires separate assumptions and analysis. KKT-based reformulations need suitable lower-level conditions; a MILP reformulation supports a global-optimality claim only when equivalence and solver certification are established. Heuristic solutions instead require appropriate feasibility and optimality-gap evidence. The label "Stackelberg game" alone establishes neither uniqueness nor incentive compatibility.

5.1.2. Leader-Follower Games Between VPP Operators and Internal DERs

As illustrated in Table 8, the internal operations of a VPP involve complex interest interactions among the operator and distinct independent DER entities, such as DR aggregators, EV users, and ESS owners. To address this issue, two distinct optimization dispatch architectures have been constructed in existing literature based on the differentiation of decision-making leadership: the VPP operator-led framework and the internal DER-led framework.

Within the decision-making architecture centered on the VPP operator, the responsibility for formulating internal transaction prices or incentive mechanisms lies with the operator. Conversely, internal DER entities act as followers, responding to price signals based on the principle of individual utility maximization. For instance, a framework characterized by VPP operator leadership and DR aggregator response was constructed by Wei et al. [188] where SP and RO algorithms were combined to address multiple uncertainties, with the solution derived via the C&CG algorithm. Simultaneously, utility functions were introduced by Zhao et al. [189] to quantify the charging satisfaction and costs associated with EV users, utilizing SP to manage the power output volatility of renewable energy. The typology of lower-level resources was further expanded by Maiz et al. [190], encompassing a diverse range of assets from DGs to controllable loads. The primary advantage of such models based on analytical methods lies in the rigor of mathematical derivation; however, their application is strictly constrained by the convexity conditions of

the lower-level models. Motivated by privacy protection considerations, the conventional KKT condition transformation was discarded by Chang and Yang [44] within the same VPP operator-led architecture. Instead, a bisection method combined with a distributed iterative strategy was adopted for solution generation. In this study, physical isolation of upper- and lower-level data was effectively realized, while simultaneously utilizing risk-averse SP to address uncertainties associated with PVs, WTs, loads, and prices.

In the decision-making architecture centered on DER entities, DER agents function as leaders, prioritizing the optimization of their own bidding strategies to maximize profit. The VPP operator, acting as the follower, is responsible for market clearing and system balancing. To resolve such hierarchical optimization problems, KKT conditions have similarly been employed in relevant research to convert bi-level models into single-level problems. For example, a framework led by DER agents with VPP operator response was developed by Liu et al. [191]. In this approach, chance constraints were utilized to handle the uncertainty of renewable energy output, and the solution was achieved through KKT conditions combined with an improved C&CG algorithm.

Furthermore, heuristic algorithms have been adopted in some studies as a supplement to address the interesting interactions between the VPP and internal DERs. A hybrid nutcracker optimization algorithm coupled with quadratic programming was utilized by Shui et al. [192] to resolve multi-agent coordination problems involving carbon-handling aggregators. Departing from the traditional leader-follower perspective, the problem was viewed by Qi et al. [193] as a collaborative optimization among multiple stakeholders. Here, the non-dominated sorting genetic algorithm II was applied to simultaneously enhance the comprehensive benefits of the VPP, ESSs, and consumers. Although these methods effectively circumvent complex mathematical transformations and improve model adaptability to non-linear physical characteristics, they are slightly inferior to analytical methods regarding the proof of global optimality of the solution.

5.2. Cooperative Game

Non-cooperative game theory is utilized to address the maximization of individual payoffs through competitive strategies, whereas cooperative game theory is focused on the equitable distribution of collective gains following optimal dispatch. The stability of a coalition of VPPs relies heavily on the provision of sufficient economic compensation for the members, as inadequate incentives often lead to the dissolution of the alliance. Upon the securement of total market revenue, the design of a profit allocation mechanism becomes essential. This mechanism must account for the contribution, the risk profile, and the bargaining power of each member to ensure long-term fairness. By establishing distribution rules, cooperative frameworks effectively mitigate the risk of fragmentation caused by internal profit imbalances. Current literature primarily classifies these cooperative approaches into three categories: the Shapley value, the nucleolus method, and the Nash bargaining solution.

5.2.1. Profit Allocation Method Based on Shapley Value

The Shapley value is defined as the weighted average of a participant's marginal contributions across all possible sequences of coalition formation. Given its adherence to the axioms of uniqueness and efficiency, this method is widely adopted to resolve problems associated with heterogeneous resource allocation. Building upon this theoretical foundation, Fang et al. [194] employed particle swarm optimization to address day-ahead VPP scheduling while accounting for distributed units and thermal-electric network topologies. They further proposed an enhanced Shapley value method for multi-stakeholder profit

allocation by embedding individual differences into the weighting parameters, yet the underlying VPP structure in their study remained simplified.

In a similar vein, Liu et al. [195] developed a cooperative game model for VPPs participating in energy, ancillary services, and carbon markets. Their approach utilized a modified Shapley value considering forecasting accuracy and environmental impacts to distribute profits among DERs, though the VPP configurations and DER models were relatively basic. Additionally, Ju et al. [196] formulated a two-stage RO model to manage energy interactions among multiple VPPs. This research transformed a bi-level optimization into a single-level equivalent via strong duality theory and applied the C&CG algorithm for its solution. By incorporating structural and functional indicators, they utilized the incremental benefits of cooperating entities as weighted eigenvalues to facilitate profit allocation among the various VPPs.

5.2.2. Profit Allocation Method Based on Nucleolus Method

The nucleolus method identifies the most robust allocation solution by lexicographically minimizing the excess vector of a coalition, which effectively minimizes the maximum dissatisfaction among all potential sub-coalitions. Nguyen and Le [197] addressed the cost allocation problem for VPP aggregators managing multi-party demand resources by developing a bi-objective optimization framework. This framework facilitates an effective trade-off between stability and fairness in the nucleolus-based cost allocation through the joint application of the ε-constraint method and row generation to construct the Pareto front. While the study incorporates a risk-averse model to account for uncertainties in renewable energy, rigid loads, and market prices, the underlying DER models remain relatively simplified.

5.2.3. Profit Allocation Method Based on Nash Bargaining Solution

The Nash bargaining solution identifies an optimal compromise acceptable to all parties by maximizing the product of their utility increments relative to a disagreement point, a value commonly referred to as the Nash product. Building upon this concept, Yan et al. [198] proposed a multi-VPP energy sharing model that decomposes the problem into two distinct sub-problems, specifically the minimization of total coalition costs and the allocation of peer-to-peer transaction costs. Although their study utilized the alternating direction method of multipliers (ADMM) and an exponential mapping approach for the solution, the underlying DER models were simplified and neglected the impact of uncertainties. In another study, Chen et al. [49] investigated joint bidding strategies for wind farms and VPPs aggregating rooftop PVs and batteries to maximize collective profits. Their work incorporated a battery capacity degradation stress model centered on the DoD and applied the Nash–Harsanyi bargaining scheme for profit distribution, noting that the specific focus on frequency regulation eliminated the need for equivalent problem transformation.

Furthermore, Wang et al. [199] established a collaborative optimization framework for integrated VPP and power-to-hydrogen systems based on the Nash–Harsanyi bargaining game while addressing renewable energy and load uncertainties through SP. To reflect the bargaining power of participants and protect operator privacy, the model was reformulated into cost minimization and bargaining payment sub-problems and solved via an enhanced ADMM algorithm, offering significant reference value regarding model complexity and uncertainty management. Du et al. [173] further developed a multi-time-scale coordination framework for VPPs and virtual hydrogen power plants covering day-ahead, intraday, and real-time operations. This model employs multi-scenario SP and chance-constrained programming at different stages to mitigate forecast uncertainty, subsequently decomposing

the day-ahead and intraday problems into coalition interest (or adjustment cost) and energy transaction payment components for resolution through the ADMM algorithm.

Cooperative allocation mechanisms distribute a coalition value calculated from the operating model. Additional surplus and coalition stability must be established against feasible outside options; neither follows from applying an allocation rule alone. Large memberships can make exact marginal-contribution calculations expensive, while simplified resource models can distort the surplus to be allocated. A further requirement is a consistent settlement benchmark across scheduling timescales and forecast revisions. These considerations should accompany comparisons of fairness, stability, and computation time.

5.3. Mixed Game

Although cooperative and non-cooperative game-theoretic approaches address distinct challenges in VPP operations, the inherent complexity of modern energy systems frequently necessitates a mixed game framework. By integrating multi-level game logic, such hybrid frameworks facilitate the unified modeling of both internal and external interaction processes within the VPP. This paradigm typically utilizes Stackelberg games to characterize the relationship between price signaling and strategic response among DSOs, VPP managers, and various levels of aggregators. Concurrently, it incorporates cooperative mechanisms such as the Shapley value or Nash bargaining to ensure equitable profit distribution within sub-coalitions. By leveraging solution strategies including the ADMM, bisection methods, and hybrid heuristics, this architecture simultaneously manages market competition, demand-side response, and multi-party profit sharing. Consequently, it establishes a comprehensive scheduling system spanning from top-level pricing to bottom-level revenue settlement. Wu et al. [200] established a bi-level game model where the VPP operator serves as the leader while load and energy aggregators act as followers. This study combined an iterative approach with the non-dominated sorting genetic algorithm II and a genetic algorithm to determine the optimal scheduling strategies and pricing for the aggregators. To ensure equitable profit distribution within the energy aggregators, the researchers utilized the Shapley value and addressed the impact of renewable energy uncertainty on scheduling via interval estimation theory. However, the VPP structure and DER models in this study remained relatively simplified. In a broader context involving end-users, Xu et al. [201] proposed a multi-leader multi-follower Stackelberg game model to characterize the interactions between multiple VPPs and energy users. Users were first clustered based on their operational preferences and energy demands, after which the Stackelberg model simulated the competitive dynamics between the VPP coalition and energy users. The optimal pricing strategies for the VPP coalition and the corresponding energy demand strategies for users were determined using the ADMM and an asynchronous gradient descent iterative algorithm. The final profit allocation was executed according to the marginal contribution of each VPP within the coalition, with the primary contribution of the research being the application of these specific solution methodologies.

Additionally, Ling et al. [202] introduced a hybrid game model led by a DSO, with multiple VPPs and shared ESSs collaboratively participating in energy and reserve markets. The overall framework follows a Stackelberg game structure in which the upper-level DSO maximizes profit by setting energy market prices while the lower-level VPPs and ESSs formulate their scheduling strategies as followers. Within the lower level, the profit allocation between the VPPs and ESSs was modeled as a Nash bargaining problem. The study employed the bisection method to traverse the price signals between the upper and lower levels and utilized the ADMM algorithm to solve the profit allocation problem, which was decomposed into cost minimization and bargaining payment sub-problems. Although this

model is relatively straightforward and neglects uncertainty, it offers significant reference value for solving hierarchical pricing and allocation problems.

Mixed game frameworks connect hierarchical strategic decisions with cooperative allocation. Their value depends on whether equilibrium, allocation, and physical operating assumptions are mutually consistent; a nested structure does not itself establish greater surplus or stable cooperation. Computational effort also depends on the subproblem structure, update sequence, and convergence conditions. Comparisons should therefore assess feasible operating outcomes and participant incentives as well as the convergence of the solution algorithm.

6. Distributed Optimization and Learning-Based Scheduling

Scheduling implementation must respect the resource, market, and incentive assumptions established in Sections 2–5. This section examines distributed optimization and DRL as ways to implement such decisions at scale. The comparison concerns information exchange, constraint handling, computation time, and validation; it does not assume that a decentralized or learning-based architecture is inherently superior.

6.1. Distributed Optimization Scheduling of VPPs

Distributed optimization decomposes a coordination problem into local subproblems and exchanges selected variables. The resulting privacy depends on the information disclosed and the protection mechanism. This subsection examines ADMM-based coordination in multi-energy and multi-agent settings, with attention to model coupling and the requirements for a valid distributed solution.

Regarding multi-agent collaborative optimization, Cao et al. [203] developed a cooperative model involving multiple VPPs and load aggregators that accounts for supply-demand balance and energy-carbon interactions. Their research emphasizes innovation in profit allocation by proposing a carbon quota distribution strategy based on an improved Shapley value to balance collective coalition gains with individual interests. At the solution level, they introduced an ADMM algorithm with dynamic penalty parameters to optimize power-heat transaction volumes and determine optimal pricing. Nevertheless, because the study focuses primarily on carbon quota allocation and distributed control architectures, it does not incorporate the uncertainties associated with renewable energy and load. Within a similar cooperative game framework, Liu et al. [204] further expanded the power-heat interaction mechanisms between multiple VPPs and load aggregators. Unlike the aforementioned study, this research aggregates multi-energy equipment including natural gas and hydrogen within a single VPP and embeds carbon trading costs into the model. This complex heterogeneous energy coupling enhances the low-carbon regulation capability of the VPP. The study uses standard ADMM, whereas Cao et al. [203] employ dynamic penalty parameters. Their relative computational performance cannot be inferred without testing the algorithms on comparable problem instances, tolerances, and hardware. In contrast to these cooperative approaches, Liu et al. [119] established a non-cooperative game model considering both electricity and carbon trading markets to maximize the profits of individual VPPs. Their research utilizes the ADMM algorithm to achieve energy interaction equilibrium among multiple agents while employing a multi-time scale optimization scheduling strategy to manage load fluctuations and PV output uncertainty. Despite these advantages, the energy flow composition described in this study remains relatively simple from a physical modeling perspective when compared to the electricity-heat-gas-hydrogen coupled systems discussed in the preceding literature.

Distributed optimization exchanges selected variables to coordinate subproblems, which can reduce central data requirements and permit parallel computation. These fea-

tures do not by themselves guarantee privacy or fast convergence. Performance depends on model structure, penalty settings, stopping tolerances, and communication reliability. Comparisons should report residuals, solution quality, communication volume, and elapsed time under common assumptions; variable exchange may still disclose information about individual participants.

6.2. DRL Scheduling of VPPs

DRL approximates decision policies from interaction data and may offer short online inference times after training. However, training effort, state and action design, and physical constraint enforcement remain part of its cost and applicability. Table 9 compares problem settings, architectures, and experimental practices. It should be read alongside the resource and market assumptions, rather than as a ranking of algorithm names.

Table 9. Comparison of problems, methodological architectures, and experimental practices across DRL-related works for VPPs.

Ref.	Problem	Technical Pathway	Methodological Architecture	Experimental Practice Analysis
[205]	Inaccurate parameters and unknown dynamic characteristics in frequency regulation	Hybrid drive with offline pre-training and online fine-tuning	Sharpness-aware minimization soft actor-critic	Split a test dataset and used ten to twenty random seeds independently to report average rewards
[206]	Power flow security violations under worst-case contingencies	Safe reinforcement learning with Lagrangian relaxation	Lagrangian soft actor-critic	Lacked explicit validation split but ran ten random seeds independently and reported cumulative rewards
[207]	Accurate extraction of non-linear user DR features	Neural Turing machine-enhanced data-driven approach	Prioritized experience replay deep deterministic policy gradient	Split the dataset for noise testing and reported root mean square errors without multiple random seeds
[208]	Internal price constraints and spatial-temporal balance in microgrids	Hierarchical architecture decoupling pricing and energy management	Hierarchical DRL	Split the test set nine to one and recorded average rewards without multiple random seeds
[209]	Computational failure due to massive decision space in coordination	Mean-field theory combined with lower-level mathematical programming	Mean-field reinforcement learning and MILP	Only compared average operating costs without dataset splitting and multiple random seeds
[210]	Input dimension variation caused by buildings dynamically joining	Adaptive transformer capturing spatial-temporal correlations	Adaptive multi-agent reinforcement learning	Possessed validation protocols and ran three random seeds independently to report average rewards
[211]	Multi-segment bidding strategies and impact on prices for price-makers	Centralized training and decentralized execution for stability	Multi-agent twin delayed deep deterministic policy gradient	Lacked validation split and multiple random seeds and error standard deviation reports

Table 9. *Cont.*

Ref.	Problem	Technical Pathway	Methodological Architecture	Experimental Practice Analysis
[212]	Economic viability boundaries and profit equilibrium points	Soft link model-driven sensitivity evaluation protocol	Multi-agent deep deterministic policy gradient	Divided training phases and reported root mean square errors while analyzing an unspecified number of random seeds
[213]	Non-convex decision-making under partially observable community environments	Partially observable Markov game model construction	Partially observable Markov decision process and multi-agent reinforcement learning	Employed an independent test set and compared average rewards without multiple random seeds
[214]	Node voltage and power flow security boundaries in coordination	Neighborhood communication guided distributed safety projection	Communication-based independent twin delayed deep deterministic policy gradient	Compared algorithm average rewards but lacked explicit validation split and multiple random seeds
[215]	Privacy leakage and data silos during parameter transmission	Federated learning combined with local differential privacy	Federated reinforcement learning	Reported cost mean and variance but lacked validation split and multiple random seeds

In practical applications, adherence to categories of constraints is required for VPP scheduling. Network limits, including the N-k contingency-based power flow security in [206] and the voltage safety boundaries in [214], are maintained. Inter-temporal storage constraints involving the evolution of the SoC are resolved through hierarchical decoupling or federated learning frameworks [208,215]. Discrete logic constraints, such as coordination logic [209] and the dynamic participation of building clusters [210], are also addressed. Additionally, market-driven bidding games under uncertainty are investigated in [207,211–213].

Constraint handling in the reviewed studies includes safe-learning formulations [206,214], optimization-assisted policies [205,209], and hierarchical or partially observable architectures [208,213]. These approaches have different enforcement mechanisms. Penalties or Lagrangian terms alone do not establish zero violations; projection or an optimization layer requires its own feasibility conditions. Thus, the constraint-handling descriptions in Table 9 should be linked to reported violations and the conditions under which protection was evaluated.

Table 9 also identifies differences in experimental reporting. Studies [205,206] report 20 and 10 random seeds, respectively, and [210] reports three; these counts describe the cited experiments rather than establish statistical significance by themselves. Training/test separation is discussed in [208,210,211], while validation-set reporting remains uneven across the listed studies. A reproducible comparison should report data splits, variability across seeds, constraint violations, inference and training times, and performance outside the training conditions. High reward alone does not establish physical feasibility or economic optimality [206,214].

Table 9 guides implementation choices through the required evidence, rather than reward values alone. For dispatch with strict operating limits, the relevant checks are feasible actions, inference latency, and behavior outside the training conditions. Optimization-assisted policies also require assessment of the optimization layer and its computation cost. Multi-agent policies require communication and coordination tests. A useful baseline is a

feasible scheduling model using the same resource limits, observations, and settlement rules. Reporting failures together with achieved net returns makes the practical trade-offs visible.

7. Research Gaps and Future Directions

The preceding comparisons identify gaps at the interfaces between resource representation, market commitments, uncertainty, and participant coordination. Evaluating these interfaces together requires device trajectories, settlement conditions, and participant responses under compatible assumptions. Access to these inputs and to controlled operating tests can constrain validation across the full decision chain. A useful improvement is to develop shared test cases, then assess economic outcomes and delivery failures through staged hardware or field evaluation. The priorities below concern gaps in model connections and validation evidence identified in the reviewed studies.

7.1. Resource Modeling and Flexibility Validation

A central modeling gap is the validation of aggregate flexibility against the underlying devices. More detail is useful only when it captures constraints that affect delivery, such as battery degradation, EV availability, thermal comfort, and ramping. Future work should compare aggregate feasible regions with detailed models or measurements across representative operating states. Relevant indicators include delivery error, comfort or equipment-limit violations, and computation time. This would show where simplified models remain adequate and where refinement changes the service capability.

For demand-side portfolios, a promising direction is to identify state-dependent power and energy boundaries that retain internal thermal or process dynamics. These boundaries should be tested when weather, occupancy, participation, and baseline demand change. Quantifying aggregation error and communication requirements would help determine whether an externally simple model remains reliable for control, rather than assuming that simplification preserves flexibility.

7.2. Service Commitments and Coupled-Market Rules

A market-modeling gap is the consistent representation of commitment timing, procurement, activation, and settlement. Frequency regulation may be procured ahead of physical delivery, even though the control response is real time; capacity arrangements and product eligibility are jurisdiction-specific. Future joint-bidding models should reserve shared power and energy capability across services and include the applicable performance scores, deviation charges, and degradation costs. Evaluation should report net revenue after these costs and penalties, together with delivery failures and capacity conflicts.

Coupled electricity, carbon, gas, hydrogen, heat, and cooling models also need explicit conversion constraints and accounting boundaries. Additional products do not necessarily create realizable surplus if conversion losses, network limits, certificate eligibility, or overlapping environmental claims are omitted. Comparisons under a common market-rule set and resource portfolio would help isolate the value of coupling from changes in modeling assumptions.

7.3. Uncertainty Calibration and Scheduling Evaluation

VPP scheduling should account for relevant uncertainties in both physical resources and market conditions. SP, RO, and DRO can accommodate resource and market uncertainties, subject to the selected information structure and problem formulation. Their suitability depends on the available distributional information, risk preferences, recourse structure, and computational requirements. When uncertain prices interact with uncertain quantities or decision variables, the resulting coupling may require reformulation, approximation, or

decomposition. Rolling-horizon optimization provides a complementary updating framework; it does not itself remove non-convexities arising from device, network, or market models. Hybrid approaches should therefore be assessed by their effect on feasibility, risk exposure, and solution time rather than by the number of techniques combined.

A remaining gap is the calibration of uncertainty models when observations are scarce, dependent, or affected by changing user behavior. Future work should disclose how scenarios, uncertainty sets, and ambiguity sets are constructed, then evaluate them on held-out periods and stress conditions. Violation probability, tail cost, solution time, and sensitivity to calibration parameters should be compared under the same resource and market assumptions. Rolling policies additionally need tests of forecast updates, delayed measurements, and the time available for each dispatch decision.

7.4. Participant Incentives and Scalable Implementation

Coordination studies often evaluate aggregate profit separately from the incentives and costs required to sustain cooperation. Future allocation models should use the same operating and degradation costs as the scheduling model and test budget balance, individual rationality, and coalition-deviation incentives under uncertainty. For distributed implementations, communication delays, stopping errors, and information disclosure should be evaluated alongside solution quality; exchanging fewer variables does not by itself establish privacy.

For DRL, the main validation gap concerns constraint enforcement and generalization beyond the training environment. Reproducible studies should specify training, validation, and test periods; report multiple seeds and infeasible episodes; and compare policies against feasible optimization baselines. Tests under unseen weather, prices, participation levels, and communication conditions should measure violations, net cost, and online latency. These checks would clarify when learning supports reliable scheduling and when an optimization or safety layer remains necessary.

7.5. Application Examples and Method Selection

Published application studies illustrate why VPP methods should be selected as connected components. Shared storage participation in energy and regulation markets [48] links access to flexibility with bidding and profit sharing. Heat pump aggregation for flexible ramping [80] shows how equipment and comfort constraints shape available services. Bidding for frequency control that accounts for battery life and cooperative allocation [49] highlights the dependence of distributable profit on operating costs.

These examples suggest that method selection should start from the intended service and its physical delivery requirements. Market commitments should reflect feasible resource capabilities, uncertainty management should account for available information and delivery risk, and allocation should distribute the surplus calculated using consistent operating and cost assumptions. Reported benefits should therefore be interpreted alongside these assumptions and the simulation conditions.

7.6. Cyber-Physical Deployment and Behavioral Validation

Practical deployment requires evidence beyond scheduling simulations [86]. Cybersecurity is one concern: false data injection into information used for DER coordination can mislead control, as demonstrated in Functional Mock-up Interface-compatible cosimulation [216]. Future VPP studies should specify compromised signals and attacker capabilities, distinguish malicious data from ordinary forecast errors, and assess detection together with fallback operation. Relevant outcomes include undetected delivery errors, constraint violations, false alarms, and recovery time.

A second concern is the interface between scheduling and fast control [105,106]. Remote hardware-in-the-loop work shows why communication latency and inverter response need explicit characterization [217]. Real-time controller- and power-hardware-in-the-loop tests could expose delayed telemetry, packet loss, actuator saturation, and active/reactive-power coupling omitted by steady-state schedules. Testing should connect these conditions to tracking error, stability, and service-delivery limits; this review does not report new hardware experiments.

Third, controllable demand depends on voluntary participation. Prospect-theoretic participation games show that subjective behavior can change load shifting relative to conventional rational-choice models [218]. Behavioral game theory is therefore a candidate extension for VPP incentives, but its parameters require calibration rather than assumed universal values. Future comparisons should evaluate participation predictions, comfort, dropout, and delivered flexibility on held-out observations while retaining device and network constraints.

Finally, market commitments must remain compatible with applicable interconnection rules. Institute of Electrical and Electronics Engineers Standard 1547-2018 provides an interconnection and interoperability framework for DERs where adopted [219]. Local grid codes, approved settings, and connection agreements determine the relevant operating limits; the standard is not a universal regulatory obligation. Connecting these limits and validated control responses to aggregate flexibility would strengthen the basis for applying bidding and allocation models.

8. Conclusions

The main implication of this review is that VPP methods should be assessed as connected decision components. Resource modeling defines deliverable flexibility, market mechanisms determine its value, uncertainty management shapes the associated commitments and risks, and benefit allocation affects participant incentives. Improvements at one stage may not translate into reliable operational benefits if inconsistent assumptions are retained elsewhere. The application examples illustrate these connections while also showing the limits of the available simulation evidence. Future comparisons should report resource constraints, market assumptions, uncertainty calibration, and validation conditions explicitly, so that methodological gains can be distinguished from gains attributable to different modeling choices.

The priorities that follow are therefore practical: validate aggregate resource boundaries; compare bidding strategies under consistent rules and costs; calibrate uncertainty models using held-out outcomes; and assess allocation and implementation methods through incentives, violations, and computation time. These priorities define a basis for comparable future studies rather than establish a universal performance ranking. Field validation remains necessary where the available evidence is confined to simulations.

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