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Review

Comprehensive Overview of Virtual Power Plants: Integration of Distributed Energy Resources into Power Systems in Terms of Aggregation, Application, and Innovation

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Abstract

As modern power systems undergo a paradigm shift toward decentralization, driven by substantial investments in Distributed Energy Resources (DERs), Virtual Power Plants (VPPs) have emerged as the primary mechanism for their effective technical and commercial integration. This paper provides a seminal and comprehensive literature review, dissecting the VPP ecosystem through operational, infrastructural, and coordination strategy perspectives. By categorizing VPPs into distinct technical and commercial frameworks, this study critically evaluates their role in optimizing smart grid components, including demand response, multifaceted market structures, cooperative game-theoretic behaviors, and multi-carrier energy systems. The analysis transcends basic infrastructure, focusing on the resolution of fundamental challenges: mitigating carbon emissions and energy costs, characterizing generation uncertainty and asynchrony, and maintaining the dynamic equilibrium between supply and demand. Furthermore, the review explores advanced strategies for incentivizing prosumer engagement, enhancing market pricing transparency, and ensuring transaction integrity within rigorous operational constraints. A significant methodological evolution is identified, highlighting the transition toward advanced mathematical frameworks and data-driven optimization techniques designed to enhance system resilience and operational stability under multifaceted uncertainties. The synthesis reveals that VPP-led sector coupling integrating electricity, thermal, and hydrogen vectors provides a robust pathway for minimizing grid imbalances and diminishing the overall carbon footprint. By evaluating the subject through a multidimensional lens—technical, economic, environmental, and regulatory—this study serves as a critical reference and strategic roadmap for researchers, planners, and policymakers aiming to navigate the complexities of future smart grids and build a sustainable energy ecosystem.

Keywords: aggregation; carbon emission; carbon mitigation; demand response; Distributed Energy Resources (DERs); multi-energy systems; prosumer engagement; smart grid; uncertainty management; Virtual Power Plant (VPP)

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1. Introduction

The electrification of the global energy infrastructure is intensifying, with electricity assuming an increasingly central role in modern power systems. Driven by burgeoning requirements for heating, cooling, electric mobility, and the rapid expansion of data centers, global electricity demand is experiencing sustained growth, particularly in emerging economies. Relying on fossil fuels to meet this escalating demand remains the primary driver of global carbon emissions. Nevertheless, the transition toward sustainable energy is gaining significant momentum; 2023 witnessed the integration of over 560 GW of renewable capacity into global power grids, with total investments in clean energy reaching USD 2 trillion [1]. According to the Global Energy Review 2025, the year 2024 represented a complex juncture for global energy systems, characterized by both accelerated structural transformations and mounting short-term pressures. A defining dynamic of this period has been the surge in energy demand, which has surpassed the average growth rates recorded over the past decade. This growth is primarily led by the power sector, influenced by factors such as record-breaking temperatures, intensified industrial consumption, the electrification of transportation, and digital transformation. Notably, electricity demand increased by 4.3%, nearly twice the rate of total energy demand, reflecting systemic shifts toward electrified industrial processes and the burgeoning energy requirements of artificial intelligence and data center infrastructures. The power sector accounted for three-fifths of the total increase in global energy demand. While this unprecedented rise in demand presents substantial challenges for energy security and grid stability, it simultaneously offers a critical window for accelerating the shift toward low-emission generation. 2024 emerged as a landmark year, consolidating the dominance of low-carbon sources in the global supply mix. The fact that the vast majority of the record growth in electricity generation was met through clean energy technologies is a clear indicator of the concrete steps being taken toward deep decarbonization. This transition is strategically vital, impacting not only climate objectives but also energy security and technological competitiveness. The ascendancy of clean energy is underscored by empirical data: renewables and nuclear power collectively accounted for 80% of the growth in global electricity generation in 2024. Consequently, the share of renewables in total production reached 32%, rising to 40% when integrated with nuclear power. This expansion was primarily driven by a record 700 GW of renewable capacity additions, a 30% year-over-year increase, with solar photovoltaics (PV) comprising approximately 80% of this new capacity [2].

The ongoing energy transition, characterized by the displacement of fossil fuels with renewable energy sources, is fundamentally reshaping the global decarbonization landscape. Within this framework, nations are intensifying their efforts to honor the commitments stipulated under the Paris Agreement [3]. Aggregate investment trends in power systems indicate a robust and continuous increase in the grid integration of decentralized renewable energy resources as primary alternatives to conventional generation [1]. While the proliferation of Distributed Energy Resources (DERs) offers significant advantages, including carbon footprint reduction, waste heat utilization, enhanced power quality, and improved system reliability, it also necessitates more sophisticated management and control frameworks. Compared to traditional synchronous generators (rotating machines), conventional power systems face substantial operational challenges in managing a vast number of small-scale DERs due to their distinct control topologies, management requirements, and inherent physical characteristics [4]. To mitigate these challenges and streamline the operation of renewable assets, the concept of the Virtual Power Plant (VPP) has been introduced. VPPs aggregate DERs, energy storage systems (ESS), and controllable loads into a single, unified operational entity [5]. As small-scale DERs, storage units, and flexible loads often “invisible” to system operators due to high regulatory overheads become increasingly prevalent, VPPs have emerged as a state-of-the-art solution for their

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seamless integration into the distribution grid [6]. Through the VPP architecture, renewable sources are integrated with flexible assets such as dispatchable generation units (DGUs) and storage modules. This integration not only enhances the overall stability and market competitiveness of prosumers but also provides the necessary scale for these entities to participate effectively in wholesale electricity markets [7]. Furthermore, VPPs play a pivotal role in establishing a "win–win" scenario for both upstream and downstream prosumers by forming strategic alliances that mitigate the adverse effects of intermittent renewable generation on grid security and stability [8].

Maintaining the stability and reliability of the electrical power grid remains a cornerstone of modern infrastructure. The crux of this reliability lies in "resource adequacy" the capability to provide sufficient power during peak demand periods. Securing this capacity requires massive capital investment. Given that the adoption of DERs is projected to surge over the next decade, the grid's requirement for adaptability toward variable generation will become even more acute. This expansion of renewables necessitates additional flexibility in load balancing and resource adequacy to address the mismatch between fluctuating supply and demand. Moreover, the increasing frequency of extreme weather events, cybersecurity threats, rising energy costs, and the economy-wide push for electrification present contemporary hurdles for grid planners and operators. In this context, VPPs stand out as a flexible and scalable solution capable of optimizing key performance indicators, including reliability, affordability, decarbonization, public health, equity, and active consumer participation [9]. These indicators are presented in Figure 1 along with their visuals and explanations.

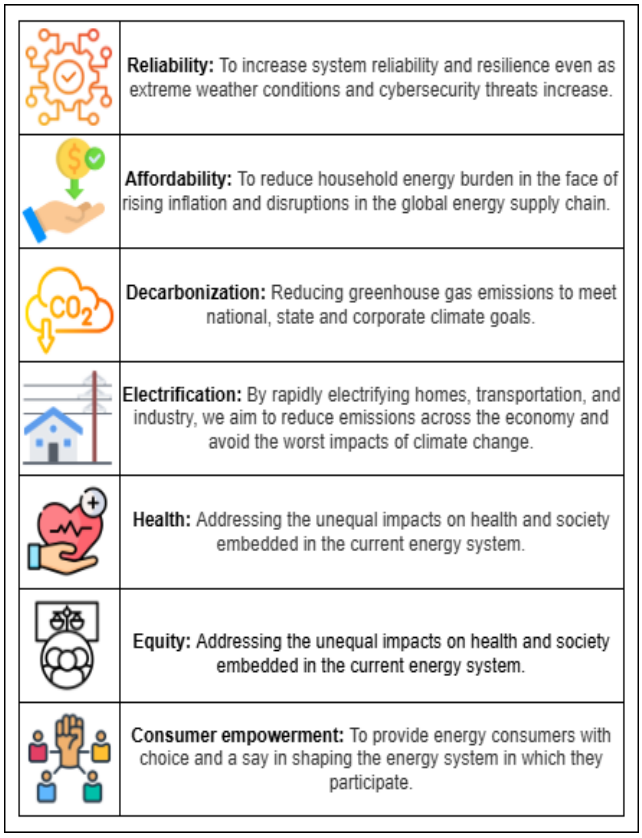

Figure 1. Power system performance targets for electrical power grid planners, regulators, and operators [9].

By mitigating the operational uncertainties associated with the intermittent performance of individual DERs, VPPs contribute significantly to the stability and overall efficiency of power systems, thereby ensuring a more reliable and sustainable energy supply

[10]. Improving the operational efficiency and economic viability of VPPs necessitates the development of sophisticated scheduling and dispatch strategies. Such advancements align with the global shift toward a low-carbon economy and the overarching goals of sustainable development [11]. Furthermore, VPPs facilitate the integration and coordination of DERs by assisting system operators in managing bi-directional fluctuations between energy supply and consumer demand, which reinforces the holistic stability of the power infrastructure [12]. Finally, by optimizing the operation of flexible assets, particularly electric vehicles (EVs) and energy storage systems (ESS), VPPs enhance both the operational efficiency and the security of distribution networks [13]. The importance of virtual power plants, which significantly contribute to the stability and overall efficiency of power systems and thus to a more reliable and sustainable energy supply, is presented in Figure 2.

Figure 2. The significance of virtual power plants.

The increasing frequency and severity of extreme weather events, driven by climate change, constitute one of the most significant threats to grid resilience. In 2023 alone, the United States experienced 28 distinct weather-related disasters, each resulting in damages exceeding USD 1 billion. These events account for approximately 75–80% of all power outages across the nation, imposing substantial economic and social burdens on both residential and commercial sectors. The vulnerability of existing grid infrastructure to such systemic shocks underscores the urgent need for more flexible and decentralized management strategies. These challenges necessitate a shift beyond conventional grid planning and capital-intensive investment models.

Virtual Power Plants (VPPs) emerge as a pivotal solution, offering a proven, rapid, and cost-efficient response to these multifaceted issues. Specifically, VPPs provide a direct and effective mechanism to address the reliability, affordability, and resilience challenges currently facing the power sector. By aggregating and coordinating rapidly proliferating Distributed Energy Resources (DERs), including rooftop photovoltaics (PV), energy storage systems (ESS), smart thermostats, and electric vehicles (EVs), VPPs can deliver grid services comparable to those of large-scale, centralized power plants. When compared to traditional infrastructure expansions, VPPs represent a more agile and cost-effective

alternative with significantly shorter deployment lead times [14]. A comprehensive mind map of the article is presented in Figure 3.

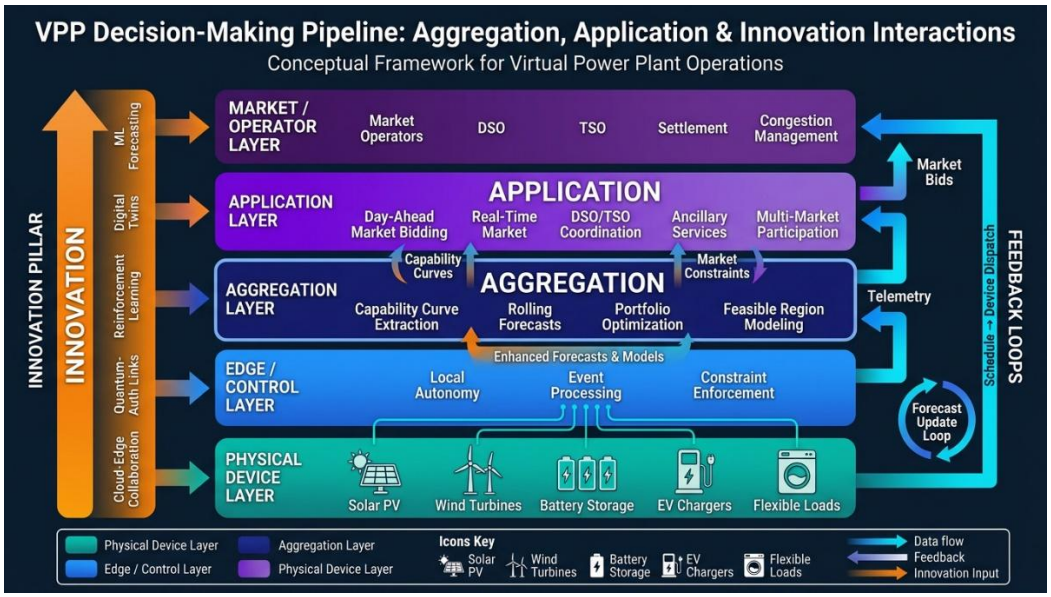

Figure 3. This article's mind map.

1.1. Motivation and Background

The global energy landscape is undergoing a fundamental paradigm shift, driven by the imperative for decarbonization and the rapid proliferation of Distributed Energy Resources (DERs). In response to international climate accords, most notably the Paris Agreement, power systems are transitioning from a centralized, fossil-fuel-dependent architecture toward a decentralized framework anchored by renewable energy [1]. This transition is largely motivated by the need to reconcile escalating energy consumption with the environmental externalities associated with conventional generation. The high penetration of DERs is now a global phenomenon, and their integration into the electrical infrastructure presents a complex trade-off between operational benefits and economic costs for various market participants [15]. The integration of DERs, bolstered by the deep penetration of renewable energy, offers significant potential to enhance overall system efficiency, mitigate transmission and distribution (T&D) losses, and reduce the carbon footprint of the power grid. However, these benefits are accompanied by increased operational complexities, such as heightened price volatility and an urgent requirement for sophisticated Frequency Control Ancillary Services (FCAS) [16]. While the shift toward decentralized power is essential for carbon mitigation, the large-scale integration of Variable Renewable Energy (VRE) sources, particularly wind and solar photovoltaics (PV), introduces formidable technical hurdles for grid operation. Unlike conventional synchronous generators, these resources lack inherent rotational inertia and exhibit highly stochastic generation patterns. This lack of predictability and physical mass creates a challenging operational environment for both Transmission System Operators (TSOs) and Distribution System Operators (DSOs) [14]. In this context, the Virtual Power Plant (VPP) framework aims to address these challenges by aggregating and optimizing DERs to ensure secure and stable grid operation while facilitating a transition toward a high-efficiency, low-carbon energy supply [11].

Efforts to address the challenges posed by the volatility of renewable energy and the complexity of optimizing multi-energy flow systems are central to maximizing renewable consumption and minimizing carbon emissions [17]. The core difficulty lies in the inherent nature of DERs. Ranging from rooftop photovoltaics (PV) to electric vehicles (EVs) and

Battery Energy Storage Systems (BESS), these resources are typically small-scale, geographically dispersed, and often remain "invisible" to the central grid operator. Their stochastic nature can lead to critical operational issues, including voltage fluctuations, reverse power flows, and a significant mismatch between peak generation and peak demand, a challenge widely recognized as the "Duck Curve" phenomenon [18]. Consequently, the traditional "supply-follows-demand" operational paradigm is becoming increasingly obsolete. To ensure grid reliability and resilience in this new era, there is a critical need for mechanisms capable of aggregating these dispersed resources and transforming them into visible, controllable, and flexible assets. This is where the concept of the Virtual Power Plant (VPP) emerges as a robust solution. A VPP acts as an advanced aggregator that leverages sophisticated Information and Communication Technologies (ICT) and software architectures to consolidate various DERs, presenting them to the grid as a single, dispatchable power plant [9]. By employing aggregation, VPPs not only mitigate the uncertainty of individual renewable sources through the diversity effect but also unlock the potential for prosumers to participate in wholesale energy markets. This aggregation capability serves as the fundamental bridge that converts non-controllable distributed generation into a reliable grid service. However, simple aggregation is no longer sufficient for modern requirements. Today's power systems demand advanced VPP applications that provide multi-layered services, including frequency regulation, voltage control, and energy arbitrage across various time horizons from day-ahead optimization to real-time control. Furthermore, the sheer complexity of managing thousands of heterogeneous assets necessitates continuous innovation. Emerging technologies, such as AI-driven predictive control, Blockchain-based peer-to-peer (P2P) trading, and Digital Twins for asset monitoring, are actively reshaping the VPP landscape [19]. Understanding the synergy between aggregation strategies, practical applications, and technological innovations is therefore essential for the future of resilient energy systems.

Driven by the dual pressures of global climate change and geopolitical volatility, the imperative to decarbonize energy infrastructures has evolved into a primary sustainable development objective. This paradigm shift necessitates the large-scale displacement of fossil fuels with renewable alternatives and the sophisticated management of Distributed Energy Resources (DERs) [17]. Furthermore, the motivation for advancing Virtual Power Plant (VPP) research is underpinned by the urgent requirement to bolster energy security, mitigate climate-induced risks, and curb environmental degradation through the strategic utilization of renewables within the demand sector [13]. Against this backdrop, the present study aims to bridge existing gaps in the literature by providing a comprehensive analysis of the grid integration of distributed energy through three fundamental lenses: aggregation, application, and innovation.

1.2. Literature Review

The scholarly landscape surrounding Virtual Power Plants (VPPs) has undergone a significant trajectory of evolution over the past decade. Initial studies in this domain predominantly focused on economic dispatch and profit optimization using simplified deterministic formulations. In contrast, contemporary research has shifted toward more sophisticated frameworks that incorporate complex grid constraints and advanced uncertainty management techniques. To provide a structured overview, the existing literature is categorized and examined herein through three primary dimensions: aggregation, application, and innovation.

1.2.1. Aggregation and Physical Capacity Modeling

Virtual Power Plants (VPPs) fundamentally address the challenge of aggregating inherently decentralized and heterogeneous Distributed Energy Resources (DERs) into a

single, controllable operational entity [18]. The literature indicates that this aggregation process transcends simple mathematical summation, requiring sophisticated modeling that incorporates both physical and operational constraints. Current research focuses on the precise characterization of the Active (P) and Reactive (Q) power capacities that a VPP can reliably offer to wholesale energy markets. Unlike static approaches, these models account for dynamic and time-dependent constraints. Defining the feasible P-Q operating region, the space within which a VPP can operate without violating grid constraints such as voltage limits and line thermal ratings, is of critical importance [19,20]. To ensure the reliable definition of these operational envelopes under uncertainty, the concept of the Robust Capability Curve (RCC) has been proposed [21]. Furthermore, novel geometric methods based on the Brouwer Fixed Point Theorem have been developed to ensure full compliance with AC power flow constraints while providing less conservative boundaries compared to traditional linear approximations [22]. Modern flexibility definitions have also integrated temporal coupling intertemporal constraints such as the battery State of Charge (SoC). Additionally, the power delivery potential of a VPP is often characterized through equivalent Virtual Generator (VG) and Virtual Battery (VB) parameters [23]. As a non-wire alternative to conventional grid reinforcements, Dynamic Line Rating (DLR) technology has been integrated into VPP optimization frameworks. By adjusting the instantaneous capacity of transmission lines based on ambient weather conditions, DLR mitigates wind energy curtailment and can expand the VPP flexibility region by an average of 18.1% [24,25]. To alleviate the computational burden associated with managing thousands of individual assets (e.g., EVs, batteries, HVAC systems), intelligent and dynamic clustering strategies are employed. Distributed Energy Storage (DES) units, for instance, are aggregated into real-time dynamic clusters based on power demand, capacity, or network losses [26]. Algorithms such as PageRank and IABC-Kmeans have demonstrated efficacy in these clustering tasks [27]. In scenarios where grid impedances or topologies are partially unknown, Input Convex Neural Networks (ICNN) allow the VPP's operational capacity to be learned directly from historical datasets. This model-free approach simplifies the optimization landscape by transforming the problem from complex Mixed-Integer Programming (MIP) into a Linear Programming (LP) format, significantly reducing the computational overhead for large-scale systems [28]. Furthermore, the thermal inertia of HVAC systems is modeled as a zero-cost flexibility resource (excluding sensor requirements). By defining these systems as Virtual Energy Storage (VES) within the VPP control architecture, grid peak loads can be reduced by 16% to 50% [29].

Beyond the physical and electrical integration of assets, the successful operation of a VPP is fundamentally predicated on its ability to recruit and retain heterogeneous resources from a competitive market. This process is increasingly characterized by a 'recruitment–participation' framework, where multiple Energy Service Providers (ESPs) compete to assemble a diverse portfolio of Distributed Energy Resources (DERs) [30].

In practice, the aggregation phase involves sophisticated contractual and incentive mechanisms designed to attract prosumers with varying risk profiles and flexibility capacities. A robust assembly process must account for the competition between ESPs, as the ability to offer superior financial rewards or lower participation risks determines the scale and reliability of the resulting VPP. Therefore, the aggregation stage should be viewed not just as a technical grouping, but as a strategic market-driven assembly that ensures the VPP's viability in the face of resource volatility and provider competition [30].

1.2.2. Implementation Strategies and Control Architectures

The success of the VPP paradigm extends beyond theoretical optimization, depending heavily on real-time physical constraints, communication reliability, and field-validated control frameworks. Operational strategies for VPPs are typically characterized by

a multi-time scale approach: day-ahead scheduling for cost optimization and real-time (RT) dispatch for error correction [31]. To mitigate forecasting uncertainties in real-time operations, Rolling Horizon Optimization (RHO) has been integrated with feedback correction mechanisms. Such hybrid approaches have demonstrated the ability to reduce supply–demand mismatches from 14.83% to 7.86% [32]. In contrast to centralized schemes, distributed control methodologies such as the Alternating Direction Method of Multipliers (ADMM) and Distributed Model Predictive Control (DMPC) are increasingly preferred to preserve data privacy and alleviate the computational burden on central coordinators [33,34]. However, the performance of these decentralized systems is often hindered by communication latencies. To address this, asynchronous distributed optimization algorithms have been developed to maintain operational continuity by estimating missing data through ARIMA and MPQP models [35,36]. VPPs must also exhibit robust resilience against cyber–physical disturbances and cascading failures. The recent literature introduces Resilience Assessment Indices and recovery strategies designed to minimize performance degradation in Cyber–Physical Systems (CPS) [37]. Furthermore, for frequency regulation tasks, cyber–physical collaborative control methods have been proposed to synchronize physical dispatch with communication constraints such as jitter and packet loss [38]. Technological architectures that facilitate the transition from theory to field application have gained significant traction. To overcome the inherent rigidity of legacy SCADA systems, decentralized IoT architectures based on Information Pipe Technology (IPT) have been designed, utilizing a two-tier (Cloud/Fog) structure to achieve ultra-low latency (<1 ms) and high-precision synchronization (1 μs) [39]. To ensure interoperability among heterogeneous DERs from various manufacturers, the IEC 61850 energy standard [40,41] has been integrated with the XMPP messaging protocol. This integration ensures that even encrypted communications maintain latencies well within grid requirements, peaking at approximately 38.5 ms [42]. Empirical validation of these frameworks is evident in pilot projects such as the StoreNet initiative in Ireland, which successfully implemented hardware-based control architectures for residential VPPs (RVPPs) combining domestic storage and PV systems [43]. Additionally, the operational feasibility of VPP management algorithms has been verified using Real-Time Digital Simulators (RTDS), proving that these complex optimizations can be executed within critical 4-s response windows [44].

1.2.3. Innovation and Advanced Optimization Techniques

The VPP literature is characterized by a continuous drive toward innovative methodologies for uncertainty management, the integration of environmental objectives, and the mitigation of market manipulation risks. Traditional Stochastic Programming (SP) and Robust Optimization (RO) are increasingly being superseded by hybrid and data-driven approaches to better handle the inherent volatility of renewable generation and market prices. Distributionally Robust Optimization (DRO) has emerged as a superior framework that bridges the gap between risk-aversion (robustness) and data accuracy (stochasticity), particularly when probability distributions are not fully characterized. By constructing uncertainty sets through metrics such as the Wasserstein distance, DRO generates solutions that are less conservative than classical RO yet more reliable than SP [45]. Simultaneously, Deep Reinforcement Learning (DRL) is being deployed to optimize complex systems with unknown internal dynamics, such as EV charging behaviors and stochastic wind/solar patterns [46]. To ensure coordination among multiple VPPs while preserving data privacy, Multi-Agent DRL (MADRL) and Privacy-preserving Hierarchical Federated Reinforcement Learning (PHFRL) frameworks have been developed [47]. The strategic decision-making capabilities of VPPs in competitive environments are extensively analyzed through Game Theory. The literature indicates that large-scale VPPs exhibiting

Price-Maker behavior can achieve 36% to 108% higher profit potential compared to traditional price-taker models [48]. This strategic positioning is also scrutinized from the perspective of Independent System Operators (ISOs) to detect market manipulations such as capacity withholding [49]. Furthermore, the formation of VPP Alliances has been shown to maximize aggregate profits [50]. To ensure the equitable distribution of these surplus gains based on the risk and contribution levels of participants, cooperative game theory solutions including the Shapley Value, Nash Bargaining Solution (NBS), and Nucleolus method are employed [51]. Finally, the operational scope of VPPs is expanding toward multi-energy systems (MES), where they engage simultaneously in electricity, heat, and gas markets [52], as well as emerging carbon trading platforms [53]. The integration of Carbon Capture Systems (CCS) is particularly noteworthy, as it enhances the operational flexibility of gas-fired units while significantly driving down emission-related costs [**ERROR! REFERENCE SOURCE NOT FOUND.**].

The paradigm shift toward decentralized energy governance has necessitated breakthrough innovations in Peer-to-Peer (P2P) trading and data privacy protocols. To automate and secure energy transactions among VPPs and prosumers within trustless environments, Dual-Layer Blockchain architectures have been proposed. These frameworks facilitate transparent energy exchange without the intervention of a central authority, ensuring high-integrity settlement processes [54]. A critical challenge in P2P energy trading is ensuring that decentralized transactions do not jeopardize the physical integrity of the grid, specifically regarding line congestion and phase imbalances. To address these grid-aware requirements, distributed constraints such as transmission costs based on "Electrical Distance" [55] and "Internal Load Vector Matrices" have been integrated into P2P dispatch models [56]. These methods ensure that local trading remains within the safe operational limits of the distribution network. Furthermore, to mitigate the privacy risks associated with centralized control where sensitive telemetry data such as load profiles and battery states are exposed, Federated Learning (FL) has emerged as a transformative solution. FL enables the training of a global optimization model while keeping raw data localized on the member nodes. Recent studies have enhanced this approach by integrating K-means clustering with FL to improve model convergence and performance across highly heterogeneous and stochastic datasets [57].

As illustrated in Table 1, while existing reviews provide a solid foundation regarding the general architecture and basic optimization of VPPs, there is a distinct lack of focus on the synergy between physical grid constraints, multi-energy integration, and high-fidelity field validation. This study specifically addresses these multi-dimensional gaps by categorizing recent advancements into three pillars: Aggregation, Implementation, and Innovation.

Table 1. Key review articles in the literature and comparative scope analysis.

Reference	Core Themes Covered in the Literature	Research Gaps Addressed in This Study
[18]	General comparative analyses of Microgrids, Smart Grids, and VPPs; classification of fundamental control topologies (Centralized/Decentralized) and cybersecurity threats.	Aggregation: Dynamic, spatial, and electrical aggregation models incorporating physical grid constraints (e.g., Dynamic Line Rating (DLR) and P-Q Feasible Region characterization). Implementation: Field validation of hardware-based applications (PLC, RTDS, HIL) and Industrial IoT architectures.
[58]	Conceptual foundations of Two-Sided Energy Markets; high-level taxonomies of VPP, Demand Response (DR), P2P, and Transactive Energy (TE) frameworks.	Innovation: State-of-the-art data-driven and hybrid uncertainty management (e.g., Wasserstein DRO, DRL, and Mean Field Games). Aggregation: Integration of multi-energy vectors (Electricity-Heat-Hydrogen) and flexibility boundary analysis.

[59]	Control strategies for power systems with high RES penetration; mitigation of low-inertia issues and analysis of sub-second grid dynamics.	Innovation: Integration of environmental market mechanisms (Carbon/Green Certificates) and behavioral modeling (Bounded Rationality, Cumulative Prospect Theory). Implementation: Strategic deployment of Industrial IoT (IPT) and protocols (IEC 61850, XMPP) for seamless market-grid co-integration.
[60]	Critical review of VPP optimization models (transition from traditional SP/RO to AI and Game Theory); identification of future challenges in multi-VPP coordination.	Aggregation: Real-time and dynamic clustering of heterogeneous assets (EV, HVAC, BESS) using advanced algorithms like PageRank and K-means. Implementation: Assessment of field tests and pilot projects based on Technology Readiness Levels (TRL).
[61]	High-level comparison of VPP architectures, components, and heuristic optimization algorithms (GA, PSO, GWO); overview of Blockchain and AI trends.	Aggregation: Geometric modeling of Robust Capability Curves (RCC) and Feasible Operating Regions to define secure market capacity. Innovation: Advanced data privacy protocols (Federated Learning, Differential Privacy) and cyber–physical resilience strategies.

1.3. Contributions and Paper Organization

The literature reviewed in this study was systematically retrieved from prominent bibliographic databases, including Google Scholar, IEEE Xplore, and Elsevier (ScienceDirect). The search queries utilized high-level keywords such as "virtual power plant", "aggregation", "microgrid", "demand-side participation", "power system optimization", and "smart grid". The identified studies were categorized based on their publication year (prioritizing the 2020–2025 period), methodological focus, and the impact factor of the publishing journal. Redundant works or those lacking a clear original contribution to the VPP paradigm were excluded from this analysis.

The synthesized literature underscores the escalating significance of the VPP concept within modern power systems. The fundamental motivation of this study is to provide a comprehensive framework that enhances the flexibility, efficiency, and sustainability of grid management systems, particularly in response to the challenges posed by the high penetration of Distributed Energy Resources (DERs), thereby facilitating the transition to a resilient energy infrastructure.

This article does not merely summarize the existing literature; it re-architects the field through three critical dimensions. The primary contributions of this work are as follows:

- Triple Perspective Integration (Aggregation-Application-Innovation): For the first time in the literature, VPP operations are systematically examined through three fundamental pillars: "Aggregation" (resource management), "Implementation" (grid and market services), and "Innovation" (AI, Blockchain, and Digital Twins). This holistic approach enables researchers to bridge the gap between technical algorithms and market requirements.
- Comprehensive and Contemporary Taxonomy: A broad methodological spectrum ranging from traditional mathematical frameworks such as Mixed-Integer Linear Programming (MILP) and Non-Linear Programming (NLP) to state-of-the-art artificial intelligence techniques like Deep Reinforcement Learning (DRL) and Federated Learning (FL) is classified based on specific application domains.
- Comparative Analysis of Uncertainty Management Strategies: The most significant hurdle for VPPs, renewable energy intermittency, is subjected to a critical analysis through the lenses of Stochastic Programming, Robust Optimization, Information Gap Decision Theory (IGDT), and Model Predictive Control (MPC). This analysis

delineates which uncertainty model is most efficient for specific operational horizons (e.g., day-ahead scheduling vs. real-time balancing).

- CyberPhysical Security and Modern Technology Roadmap: The paper provides a novel forward-looking projection that encompasses Blockchain-based P2P trading, resilient control mechanisms against cyber-attacks, and Digital Twin applications that are shaping the future of VPPs.

The remainder of this paper is structured as follows: Section 2 introduces the conceptual framework of Virtual Power Plants. Section 3 details the VPP components and DERs, while Section 4 discusses market participation and operation strategies. Uncertainty modeling and risk management techniques are scrutinized in Section 5. The architectural aspects, control mechanisms, and the integration of AI are explored in Section 6. Section 7 focuses on distribution grid integration and operational constraints. Finally, Section 8 highlights the existing challenges and future research directions, followed by the conclusion in Section 9.

2. Conceptual Framework of the Virtual Power Plant

A Virtual Power Plant (VPP) is a decentralized energy management system that facilitates the coordinated operation of geographically dispersed and heterogeneous Distributed Energy Resources (DERs), allowing them to function as a single, visible power entity within the grid [20]. The conceptual framework of a VPP is built upon four fundamental pillars: physical resource aggregation, operational classification, multi-energy integration, and digital infrastructure components. To establish a common technical ground, the core terminology associated with the VPP paradigm is summarized in Table 2.

Table 2. Glossary of terms and definitions [9].

Term	Definition
Virtual Power Plant (VPP)	Aggregations of hundreds or thousands of grid-integrated DERs that provide collective value to the power system. VPPs offer services directly to wholesale electricity markets (managed by RTOs/ISOs) and receive remuneration for providing capacity, energy, or ancillary services.
Distributed Energy Resources (DER)	The foundational units of a VPP, typically consisting of small-scale physical assets located at residential or commercial sites. Examples include behind-the-meter batteries, solar photovoltaics (PV), electric vehicles (EVs), smart thermostats, and heat pumps.
Aggregation	The process of consolidating numerous individual DER assets into a unified VPP. This can range from "tightly coupled" architectures, where the operator maintains direct control, to more "loosely coupled" frameworks.
Demand Flexibility	The capability of electricity demand to be shifted or reduced over time in response to price signals, grid conditions, or financial incentives. This is a core functional pillar of VPP operations.
Demand-Side Management (DSM)	An umbrella term for the strategies, programs, and technologies aimed at influencing consumer electricity usage patterns, serving as the historical and conceptual precursor to modern VPPs.
RTO/ISO	Regional Transmission Organization/Independent System Operator. These are independent entities responsible for managing wholesale electricity markets and ensuring the reliable operation of the high-voltage transmission grid.
Behind-the-Meter (BTM)	Refers to energy resources (such as rooftop PV or domestic BESS) located on the customer's side of the electric meter, providing power for onsite use or grid support.

The primary functional objective of a VPP is to transcend market entry barriers by consolidating small-scale assets with stochastic outputs such as photovoltaics (PV), wind turbines, batteries, and flexible loads into a single competitive entity [8]. Within this framework, heterogeneous resources are abstracted and presented to upper-level system operators (TSO/DSO) through equivalent Virtual Generator (VG) or Virtual Battery (VB)

parameters, encompassing characteristics such as active power ratings, ramp rates, and energy storage capacities [23]. To refine this representation, resources are often modeled using the Control–Uncontrollability Decomposition (CUD) approach, which bifurcates assets into flexible (controllable) and stochastic (non-controllable) components [62].

In the literature, VPPs are broadly categorized based on their primary operational mandates into two types: Commercial Virtual Power Plants (CVPP) and Technical Virtual Power Plants (TVPP). A CVPP focuses predominantly on economic profit maximization, acting as a strategic player either as a price-maker or price-taker within wholesale energy and ancillary service markets. Conversely, a TVPP prioritizes local grid constraints, such as voltage stability, thermal line ratings, and loss mitigation, operating in close coordination with the Distribution System Operator (DSO) to ensure network security [63]. The modern VPP paradigm is evolving beyond purely electrical systems into Multi-Energy VPP (MEVPP) structures. These integrated frameworks incorporate Combined Heat and Power (CHP) units, Electric Vehicles (EVs), heat pumps, and Power-to-Gas (P2G/Hydrogen) technologies [52]. A significant innovation in this domain is the integration of environmental stewardship into the optimization loop, including the tracking of carbon emission flows and the optimization of Carbon Trading and Green Certificate mechanisms [64]. VPPs assume multi-dimensional economic roles within the energy ecosystem. Through Value Stacking capabilities, they simultaneously engage in energy arbitrage while providing frequency regulation, voltage support, synthetic inertia, and fast-ramping services [65]. Furthermore, they facilitate decentralized, transparent, and secure energy exchange via Peer-to-Peer (P2P) Trading architectures underpinned by blockchain technology [64]. To sustain these cooperative structures, game-theoretic solutions like the Shapley Value and Nash Bargaining are employed to ensure the equitable distribution of surplus profits based on the risk and contribution profiles of individual participants [66]. The practical realization of a VPP necessitates a robust information infrastructure bridging physical assets and the digital control layer. Adherence to standardized and secure protocols, such as IEC 61850 and XMPP, is essential for the telemetry and control of field-level DERs [42]. State-of-the-art digital technologies, including 5G, the Internet of Things (IoT), Cloud-Fog computing, and Digital Twin applications, are critical for enabling real-time, high-fidelity control [39]. Finally, the concept of resilience defines the VPP's capacity for self-healing during natural disasters or cyber-attacks, often through autonomous transition into microgrid islanding modes [67].

As illustrated in Figure 4, VPPs serve as the unifying bridge that aggregates distributed, grid-interactive electrical devices into a coherent operational system [9].

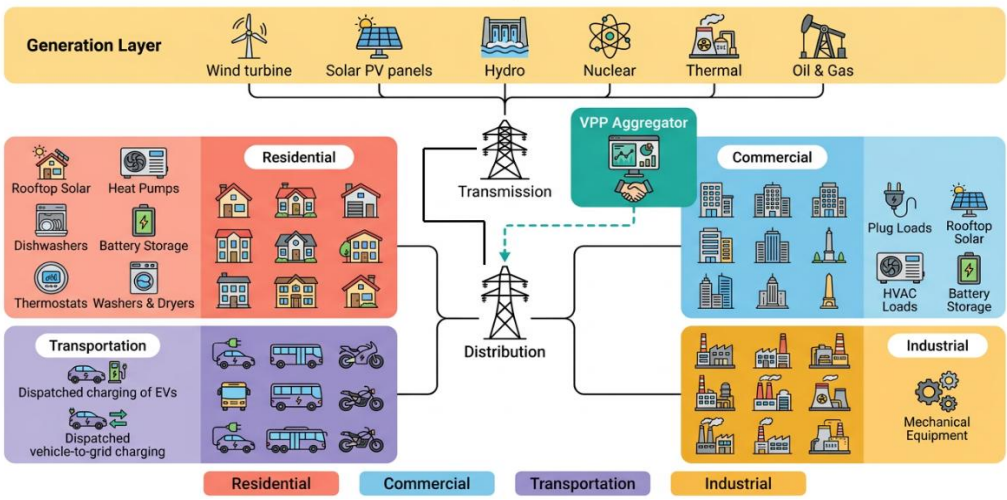

Figure 4. VPPs aggregate distributed, grid-interactive electric devices [9].

3. VPP Components: Distributed Energy Resources (DERs) and Others

Virtual Power Plants (VPPs) function as decentralized architectures that aggregate a diverse array of Distributed Energy Resources (DERs) to facilitate renewable energy integration, maintain grid stability, and optimize market participation in modern power systems [61]. The renewable energy sources that form the backbone of VPPs typically provide low-carbon and environmentally friendly generation; however, they are characterized by an inherently intermittent and stochastic nature dictated by meteorological conditions [27].

- Wind Power Plants (WPP): Wind generation often carries significant operational uncertainty. Consequently, it is coordinated with other flexible assets within the VPP framework to mitigate potential imbalance penalties and ensure reliable dispatch [68].
- Photovoltaic (PV) Systems: PV resources can range from residential to commercial scales. To manage the inherent volatility of solar irradiance, VPPs employ advanced forecasting models and demand response (DR) mechanisms [69–71]. Furthermore, hybrid Photovoltaic-Thermal (PVT) panels, which simultaneously generate electrical and thermal energy, are increasingly being integrated into the VPP ecosystem [72].

Storage systems serve as indispensable assets that enable the VPP to manage temporal supply–demand mismatches and monetize operational flexibility within the market [73,74].

- Battery Energy Storage Systems (BESS): Stationary battery infrastructures are utilized for high-speed frequency support, voltage regulation, and energy arbitrage [73].
- Thermal Energy Storage (TES): Operating in conjunction with heat pumps and boilers, TES units provide vital flexibility for district heating networks [75].
- Electric Vehicles (EVs) and Charging Stations: Within the VPP architecture, EVs are often modeled as Virtual Energy Storage (VES) units. Through Vehicle-to-Grid (V2G) technology and structured incentive programs, these mobile assets can sell energy back to the grid or perform load shifting to optimize charging schedules [76].
- Pumped Hydro Storage (PHS): For large-scale VPP operations, PHS remains one of the most economically impactful resources for storing surplus renewable energy. It allows the VPP to position itself as a “price-maker” in energy markets by managing substantial power volumes [73].

In contrast to the intermittent nature of renewables, dispatchable generation units serve as either base-load or peaking units that can be synchronized and ramped up upon the operator’s command to meet specific setpoints [77,78].

- Gas Turbines (GT) and Diesel Generators: These units are typically utilized as emergency reserves or are dispatched during high-price intervals to maximize the VPP’s profit margins through strategic bidding [77,79].
- Combined Heat and Power (CHP/CCHP): By simultaneously producing electricity and thermal energy (heating/cooling), these co-generation systems enable the VPP to participate actively in multi-carrier energy markets [80].
- Hydropower Plants: Due to their rapid response capabilities and high ramp rates, hydro units significantly enhance VPP performance in frequency regulation and reserve markets [81].

Demand Response (DR) resources provide a critical layer of flexibility by incentivizing consumers to modify their electricity usage patterns in response to grid conditions or market signals [82].

- Price-based and Incentive-based DR: Under these schemes, users reduce or shift their consumption during periods of high market prices or when provided with direct financial incentives by the VPP operator [83].
- Controllable and Interruptible Loads: These encompass industrial-scale assets, such as crushers or commercial refrigeration systems, which the VPP can directly curtail or de-energize to maintain grid stability during contingencies [84].
- HVAC Systems and Smart Buildings: The thermal inertia of building structures allows them to function as a "virtual battery." By modulating HVAC setpoints within established comfort boundaries, VPPs can achieve peak load reductions ranging from 16% to 50% without requiring additional storage hardware [85].
- Shiftable Loads: Predominantly residential, these include appliances such as washing machines or dishwashers. Their operation can be deferred to off-peak hours when electricity is cheaper, without altering the total energy volume consumed [84,86].

The heterogeneous components of the virtual power plant are visually presented in Figure 5.

The evolution of VPPs is increasingly characterized by sector coupling, wherein the VPP interacts not only with the electrical grid but also with gas and thermal networks to optimize overall systemic efficiency [80]. This multi-carrier approach enables the harvesting of synergies between distinct energy vectors, providing a more robust framework for decarbonization.

- Power-to-Gas (P2G) Conversion: This technology facilitates the conversion of surplus renewable electricity into green hydrogen or synthetic methane via electrolysis. These gaseous energy carriers can be stored long-term, injected into the gas grid, or utilized in the transportation sector, effectively serving as a high-capacity energy storage medium [26].
- Natural Gas Grid Integration: The integration with gas infrastructure allows for cross-vector flexibility transfer. This is achieved either through P2G facilities injecting synthetic gas into the network or by utilizing high-efficiency gas turbines that draw from the gas grid to support the power system during peak demand or low-RES periods [87].
- District Heating Network (DHN) Integration: VPPs coordinate the thermal and electrical sectors through Combined Heat and Power (CHP) units and large-scale electric boilers. A sophisticated innovation in this domain involves the dynamic reconfiguration of DHN topologies through valve control. By altering the flow paths within the thermal network, VPPs can significantly augment their operational flexibility and optimize heat delivery patterns [80].

Figure 5. Heterogeneous components of the virtual power plant.

Ultimately, a Virtual Power Plant functions as an integrated energy ecosystem that leverages advanced orchestration algorithms to harmonize these heterogeneous assets. By strategically balancing wind stochasticity with the rapid response of battery storage, solar intermittency with the inherent thermal inertia of building structures, and carbon footprints through green hydrogen production, VPPs establish a robust and resilient energy paradigm [29,60,64]. Recent virtual power plant (VPP) studies, including energy source classification and inter-sectoral integration frameworks, are presented in Table 3.

Table 3. Categorization of energy resources and sector-coupling frameworks in recent VPP studies.

Reference	Renewable Energy Sources (RES)	Storage Systems	Controllable Generation	Demand Response (DR) Resources	Multi-Energy Systems/Sector Coupling
[18]	Solar (PV), Wind, Biomass, Geothermal	BESS, Flywheel, Supercapacitor, Pumped Hydro, PHEV	Diesel Generator, Fuel Cell, Microturbine (CHP)	Smart Home Appliances, Controllable Loads	CHP, Thermal Systems
[23]	Wind (WT), Photovoltaic (PV)	Electrical Energy Storage (ESS)	Combined Heat and Power (CHP)	HVAC Systems (Thermal Loads), Non-controllable Loads	Partial (Includes CHP/HVAC; focus on P-Q flexibility)
[39]	Solar, Wind, Biomass	Battery (BESS)	Distributed Generation (DG)	Controllable Loads (HVAC, Lighting, Pumps)	Wastewater Treatment Plant Integration
[64]	Wind, PV	Electricity, Heat, and Carbon Storage	Gas Turbine, Gas Boiler	Integrated Demand Response (IDR)	P2G, Carbon Capture and Storage (CCS)
[69]	Wind, PV, Biowaste Units (BU)	EV Parking Lots (EVPL-V2G)	Distributed Generation (DG)	Price-Based DR (PBDR)	Waste-to-Energy (Biowaste)
[75]	Wind, PV	Battery (BESS), Thermal Energy Storage (TES)	Diesel Generator, CHP, Boiler	Residential Loads (with interruption options)	Heat and Power Integration
[76]	Wind, PV	EV Virtual Energy Storage (EV-VES)	Gas Turbine (GT)	EV Responsiveness	Carbon Trading Integration
[83]	Wind, PV	Energy Storage (ES)	Thermal Power Unit (TP)	Enhanced PBDR (Elasticity-weighted)	Joint Electricity-Carbon Market
[87]	Wind, PV	Power, Heat, Flue Gas, Carbon Storage	Coal (with CCU), CHP, Gas Boiler, Waste Incineration	Interruptible Loads, Shiftable Loads (Carbon Capture Load)	P2G, Manure Treatment System (MTS), Gas/Heat/Waste Networks
[88]	Wind (WT), Photovoltaic (PV)	Electrical Energy Storage (EES)	Combined Heat and Power (CHP)	Electrical Load, Thermal Load, Electric Boiler (EB)	Carbon Capture and Storage (CCS), Combined Heat and Power
[89]	Solar PV, Wind, Fuel Cell (FC)	Energy Storage Systems (ESS), Electric Vehicles (EV)	Combined Heat and Power (CHP), Heat-Only Unit (HOU)	EV (as flexible reserve)	Heat and Power (Combined)

[90]	Wind Farm, Solar PV	Hydrogen Storage	Open-Cycle Gas Turbine (OCGT), Fuel Cell	Interruptible Load, Electrolyzer	Power-to-Gas (P2G) (Hydrogen Integration)
[91]	Solar (PV), Wind, Fuel Cell (FC)	ESS, Electric Vehicles (EV)	Combined Heat and Power (CHP), Heat-Only Unit (HOU)	Electrical Load	Heat-Power Integration, Multi-Area Interconnection
[92]	PV	Battery (BES)	Micro Gas Turbine (MGT)	Controllable Thermal Loads (CTL)	Thermal Load Management
[93]	Wind (WT)	ESS, Electric Vehicles (EV)	Distributed Generation (DG), CHP	Residential Load, Heat Demand (Boiler, Thermal Storage)	Integrated Heat and Power (CHP, Boiler, TES)
[94]	Wind (WPP), Photovoltaic (PV)	Hydrogen Storage, Thermal Energy Storage (TES)	Biogas CHP, District Heating Plant	Electrolyzer (P2H), Electric Boiler	Hydrogen Production, District Heating Network (DHN)
[95]	Photovoltaic (PV)	Battery (Electricity Storage)	Diesel Generator, CHP	Thermal Loads (Heating/Cooling), Controllable Loads (EB, Electric Chiller)	District Heating/Cooling Integration (Heat/Cooling Bus, Gas Station)
[96]	Photovoltaic (PV), Wind Turbine (WT)	Battery Storage, Electric Vehicles (EV)	Diesel Generator, Fuel Cell	Demand Response Control (Load Forecasting)	Fuel Cell (Potential Hydrogen/Gas Integration)
[97]	Wind, PV	Battery (BESS), Hydrogen Storage	Hydrogen-fueled OCGT, Fuel Cell	Electrolyzer (as Flexible Load)	Power-to-Hydrogen (P2H/P2G)

4. Market Participation and Trading Strategies

Virtual Power Plants (VPPs) assume pivotal strategic roles across multi-layered energy markets, serving as both economic and technical interfaces within modern power systems [98]. Depending on the inherent flexibility and capacity of their constituent resources, VPPs operate across various temporal scales to maximize their economic viability. Based on short-term renewable generation and load forecasting, VPPs determine optimal energy schedules for the following day and submit competitive bids to the Day-Ahead Market (DAM) [71,99,100]. To mitigate operational deviations arising from forecasting uncertainties and to ensure system balancing, they engage in Real-Time Markets (RTM) and Intra-day Markets within second-to-minute resolutions [8,71,99,100]. VPPs generate diversified revenue streams by providing critical ancillary services, including frequency regulation, spinning reserves, emergency backup, and voltage support [51,64,77,101–104]. Furthermore, they are increasingly instrumental in delivering innovative grid products, such as Flexible Ramping Products (FRP) and Fast-Acting Reserves (FAR), which are essential for addressing rapid net-load fluctuations [105–107].

The operational objective of a VPP in a day-ahead market can be generalized as the maximization of total expected profit (Π), considering both market revenues and internal operational costs:

$$\max \Pi = \sum_{t=1}^{T} \left(\lambda_t^{DA} P_t^{VPP} + \lambda_t^{AS} R_t^{VPP} - \sum_{i \in \mathcal{I}} C_i \left(P_{i,t} \right) \right)$$

where λ_t^{DA} and λ_t^{AS} represent the day-ahead and ancillary service prices at time t, P_t^{VPP} and R_t^{VPP} are the power and reserve bids, and $C_i(P_{i,t})$ denotes the generation or degradation costs of the i-th DER unit.

The transactional landscape of VPPs involves multiple stakeholders and distinct operational models at various levels:

- VPP-to-Grid (Wholesale Trading): VPPs facilitate bulk energy exchange with the transmission grid in wholesale markets, significantly contributing to the aggregate supply–demand equilibrium [98].
- VPP-to-Retail Markets: At the distribution level, VPPs actively trade active/reactive power and reserves within retail markets, often leveraging Locational Marginal Pricing (LMP) mechanisms to reflect local grid conditions [108].
- VPP-to-DER Transactions (Internal Marketplace): To manage potential conflicts of interest among diverse asset owners (e.g., individual prosumers or third-party aggregators) within their portfolio, VPP operators establish dynamic internal pricing mechanisms and incentive structures [8,26,99–102,109].
- Peer-to-Peer (P2P) Trading and Decentralized Governance: Peer-to-Peer (P2P) energy trading represents a paradigm shift from centralized management, enabling multiple VPPs or prosumers to directly exchange energy and carbon credits [50,56,64,103–105]. Within this decentralized framework, Blockchain technology is leveraged to ensure transparency, bolster cybersecurity, and facilitate automated financial settlements through smart contracts [54,55]. The integration of P2P trading within the VPP ecosystem is instrumental in both minimizing operational expenditures and enhancing grid technical performance. By reducing reliance on centralized market structures and optimizing the utilization of local resources, P2P frameworks yield significant economic benefits. Empirical studies demonstrate that P2P mechanisms can reduce total operational costs by 7.2% to 16.77% [55,106]. In multi-energy systems (encompassing electricity, heat, and carbon), these savings can reach up to 15.2% [64]. Furthermore, blockchain-based hierarchical P2P models have been shown to lower electricity costs for end-users by 3.38% to 10.03% compared to traditional centralized governance [54]. To ensure the long-term sustainability and stability of these decentralized systems, game-theoretic approaches such as Nash Bargaining and the Shapley Value are employed. These methodologies facilitate the equitable distribution of surplus profits among participants based on their respective risk profiles and contributions to the network [50,105].

The economic behavior of VPPs in competitive environments is optimized through various bidding strategies designed to navigate market volatility:

- Profit Maximization and Cost Minimization: The overarching objective of a VPP is to maximize aggregate revenue or minimize operational overhead while operating under systemic uncertainties [45,79,84,105,107,110].
- Price-Taker Model: This model is typically adopted by small-scale VPPs that lack the market power to influence clearing prices. In this scenario, the VPP optimizes its bid-offer curves based on exogenous price forecasts [46,48,68,78,108,111–119].
- Price-Maker Model: Large-scale VPPs with significant capacity can act as price-makers, strategically influencing Locational Marginal Prices (LMP) or Market Clearing Prices (MCP) to their advantage. Such entities may even employ strategic capacity withholding deliberately restricting available supply to manipulate market prices and enhance their competitive position [49,120].

Modern VPP optimization frameworks transcend simple fuel-cost minimization, integrating a multidimensional array of operational and environmental variables to reflect the true cost of decentralized energy management.

- Supply Function Derivation (SFD): To facilitate market integration, uncertain resources particularly behind-the-meter (BTM) assets are modeled through a risk-adjusted supply function. This approach enables these resources to be presented to wholesale markets as reliable and dispatchable units equivalent to conventional generators [121].

VPP optimization models take into account not only direct fuel costs, but also a range of operational and environmental factors.

- Emission Costs and Carbon Trading: By integrating into carbon markets (e.g., CEA, CCER), VPPs monetize emission reductions while internalizing the environmental costs associated with high-carbon assets [53,83,87,122–124]. Moreover, Tiered Carbon Trading mechanisms are increasingly utilized to provide more effective signals for deep decarbonization [76,88,104,125]. To effectively participate in tiered carbon trading and joint electricity-carbon markets, VPPs must move beyond static emission factors toward dynamic Carbon Emission Flow (CEF) tracking. CEF methodologies allow VPPs to quantify the real-time carbon intensity of the electricity being dispatched or stored, considering the varying emissions of the primary energy mix across different network nodes [126]. This precise quantification is essential for validating the environmental 'additionality' of VPP actions.

Furthermore, a comprehensive evaluation of VPP sustainability requires a shift toward Life-Cycle Assessment (LCA) frameworks. The current literature often overlooks the upstream and downstream environmental costs, such as the material-intensive production and recycling challenges of battery energy storage systems (BESS) and the energy-intensive electrolysis process for green hydrogen [127]. For instance, the environmental benefit of hydrogen-based VPPs is heavily contingent upon the carbon footprint of the electricity used for electrolysis and the degradation rates of the fuel cell stacks. Integrating LCA metrics into VPP optimization models ensures that operational profits do not come at the expense of long-term ecological degradation, thereby providing a more transparent view of the 'net-zero' potential of aggregated DERs [128].

- Battery Degradation Costs: To preserve asset longevity, optimization models incorporate sophisticated battery health parameters, including Depth of Discharge (DoD), cycle life, and thermal impacts, as explicit cost components [51,58,82,109,129,130].
- Imbalance Penalties (Deviation Fees): These represent the financial liabilities incurred when a VPP's actual output deviates from its day-ahead commitments. Robust optimization frameworks are specifically deployed to mitigate the risk of such penalties, ensuring more predictable financial performance [68,77,79,102,109,131–134].
- Demand Response (DR) Incentive Payments: These are the financial remunerations distributed by the VPP operator to consumers in exchange for their flexibility in shifting or curtailing demand [84,102,125,135–141].
- Green Certificate Revenues: These encompass additional revenue streams generated through the certification of renewable energy production, such as Renewable Energy Certificates (RECs) or Guarantees of Origin (GoOs) [123,142,143].

The synthesis of market participation models, trading strategies, and economic formulations in the VPP literature is presented in Table 4.

Table 4. Synthesis of market participation models, trading strategies, and economic formulations in VPP literature.

Reference	Market Types	Transaction Models	Bidding/Trading Strategy	Cost and Revenue Components
[8]	Day-Ahead (DA), Real-Time (RT)	VPP-to-Wholesale, VPP-to-Prosumer (Internal)	Stackelberg Game (Leader-Follower), Profit Maximization	Market trading revenues, internal trading, load shedding compensation.
[45]	DAM, Real-Time Operation (RTM)	VPP-to-Wholesale, VPP-to-Retail	Profit Maximization, Price Taker	Sales revenue, RT imbalance fees, BESS degradation costs.
[48]	DAM, Reserve Market (Up/Down)	VPP-to-Grid (Wholesale)	Price Maker, Profit Maximization, Stochastic Bidding	Energy and reserve sales, reserve deployment revenue, start-up/shut-down costs.
[51]	FCAS, Demand Response (Critical Peak Rebate)	VPP Retailer-to-Consumer	Profit and Utility Maximization (Cumulative Prospect Theory)	Rebate payments, dissatisfaction costs, CO_2 reduction revenue.
[63]	Day-Ahead Market (DAM)	VPP-to-Grid, VPP-to-Customer (Retail)	Profit Maximization, Risk (Regret) Minimization	DR incentive payments, grid trading, TGU operating costs.
[64]	P2P (Electricity, Heat, Carbon)	Multi-VPP Trading	Trading Preference, Cost Minimization	P2P sales revenue, fuel costs, carbon tax, P2P transaction costs, risk cost (CVaR).
[68]	Futures Market, Day-Ahead Market (DAM)	VPP-to-Grid (Buy-Sell), Bilateral Agreements (PPA)	Profit Max., Price Taker, Two-stage Stochastic Bidding	Futures/Spot revenues, imbalance fees (failure-induced), fuel costs.
[71]	Day-Ahead (DAM), Ancillary Services (Frequency/Reserve)	VPP-to-Grid (Wholesale)	Cost Minimization, Price Taker	Imbalance fees, reserve capacity revenues, comfort violation penalties.
[79]	Wholesale Electricity Market	IVPP-to-Industrial Load (PPA), VPP-to-Grid	Profit Maximization (Investment and Operation)	CAPEX, OPEX, fuel, grid trading (buy/sell).
[83]	Spot Energy, Ancillary Services, Carbon	VPP-to-Grid, Cooperative Game	Cooperative Bidding, Profit Maximization	Energy/Ancillary revenue, CCER revenue, carbon quota costs, DR incentives.
[84]	Day-Ahead Market (DAM)	VPP-to-Grid, VPP-to-Microgrid (Coordinated)	Profit Max. (VPP), Cost Min. (MG)	Grid trading, fuel costs, DR costs.
[88]	Carbon Trading, Energy Market	VPP-to-VPP (Nash Bargaining), Intra-VPP (Leader-Follower)	Cost Minimization (Carbon-centric pricing)	Carbon tax, quota penalties, energy procurement costs.
[144]	Energy Market, Carbon Trading Market	VPP-to-Grid, Inter-regional Transfer	Operating Income Maximization	Energy/Carbon revenue, environmental costs, carbon storage cost, IL compensation.

[98]	Wholesale Market	DISCO-VPP Interaction (Internal), DISCO-to-Market	Bi-Level: DISCO (Cost Min.), VPP (Profit Max.), Price Taker	Operating costs, flexibility procurement costs, wholesale energy purchase costs.
[99]	Day-Ahead Energy Market	VPP-to-Grid, VPP-to-DER (Auction-based Local Market)	Cost Minimization, Price Taker (Exogenous Prices)	DR incentives, DG start-up/shut-down costs, grid trading revenues.
[100]	Wholesale Energy, Regulation Services	VPP-to-Grid, VPP-to-DER (Internal)	Price Maker (via Price-Quota Curves-PQC)	Market clearing revenues, DER incentive payments, load balancing costs.
[102]	DAM, RTM, Wholesale and Retail Markets	VPP-to-DERA (Internal), Wholesale-Retail Arbitrage	Two-stage Bidding (DA Plan + RT Correction), Dynamic Internal Pricing	Deviation penalties, internal pricing revenue/expense, wholesale-retail price spreads.
[107]	Day-Ahead (DA), Regulation Market	VPP-to-Wholesale, VPP-to-EV Owners (Retail)	Bi-Level Bidding (Profit Max/Cost Min), Competitive Pricing	Market revenue, charging revenue, imbalance penalties, customer attrition risk.
[111]	Day-Ahead (DA)	VPP-to-Grid, VPP-to-Local Loads	Profit Maximization, Price Taker	Electricity/Heat sales, fuel, O&M, load curtailment costs.
[114]	DAM, Reserve Market	VPP-to-Grid	Price Maker, Profit Maximization (Investment-oriented)	Investment costs, energy/reserve revenues, Capital Recovery Factor (CRF).
[119]	DAM, Real-Time (RTM)	VPP-to-User (Internal), VPP-to-Grid	Profit Max. (Leader), Cost Min. (Follower), Internal Market Price Maker	Risk costs (imbalance), energy sales revenues.
[120]	DAM, Intraday, Real-Time, Ancillary Services	VPP-to-Grid (Market Power Monitoring)	Strategic Bidding (Capacity Withholding, Arbitrage)	Energy/Ancillary sales, arbitrage revenue, penalty payments.
[121]	Wholesale Energy, Capacity, and Ancillary Services (FERC 2222)	VPP-to-Wholesale (DERA), BTM Asset Integration	Supply Function Derivation (Stepped Function), Revenue Management	Shortfall risk, opportunity cost, equipment amortization, customer compensation.
[122]	Energy Market (Day-Ahead)	VPP-to-Market (Strategic Bidding)	Strategic Bidding (Price Maker), Profit Maximization	Generation costs, load shedding costs, emissions (as objective).
[137]	DAM, Balancing Market	VPP-to-EV Charging Station Collaboration	Social Welfare Maximization, Price Taker, Minimax Regret	Deviation cost, EV incentive payments, fuel costs.
[140]	Day-Ahead (DA), Real-Time (RT)	VPP-to-Grid, VPP-to-Customer (Incentive DR)	Data-Driven Bidding, Multi-objective, Rolling Horizon	Market revenues, Personalized Incentive (CIR) payments, correction costs.
[142]	Electricity, Green Certificate (TGC), Carbon Trading	Bi-Level: Internal (VPP-User) and External (VPP-Market)	Stackelberg Game (Leader-Follower), Internal Price Maker	Emission costs/revenues, TGC revenue, CVaR risk cost.
[145]	Day-Ahead (I), Real-Time (II), General Market (III)	VPP-to-Grid (Price Taker)	Profit Maximization (Three-stage Strategy)	Energy Not Served (ENS) costs, Market Clearing Price (MCP).

[146]	Electricity, Carbon, Green Certificate	VPP-to-Grid, VPP-to-Environmental Markets	Net Profit Maximization	Electricity/Carbon/Certificate revenue, fuel, maintenance, RES curtailment fees.
[147]	Emergency/Resilience Dispatch	VPP-to-Grid (Stackelberg Game)	Cost Minimization (Follower)	Value of Lost Load (VOLL), operating costs, gas production costs.
[148]	VPP Internal Market, Grid	Two-Tier Game (Leader–Follower & Cooperative)	Profit Max (VPP), Cost Min (RIES Coalition)	RIES sales revenue, grid trading revenue, maintenance, P2G costs.
[149]	Energy, Carbon, and Green Certificate Markets	Energy Sharing (Intra-Alliance P2P), VPP-to-Grid	Cost Minimization (Alliance), Nash Bargaining (Fair Distribution)	Certificate revenue, carbon tax, robustness (risk) cost, fuel costs.
[150]	Primary Frequency Control (PFC) Ancillary Market	VPP-to-ISO	Price Taker, Profit Max, Droop-based Bidding	Availability payments, Deployment payments.
[151]	Day-Ahead Market (DAM)	VPP-to-Grid	Cost Minimization (Stochastic Bidding)	DAM sales revenue, EV charging revenue, purchase costs, imbalance penalties.
[152]	Spot Market, Intraday, Real-Time Balancing	VPP-to-EV (Energy Credit Mechanism), VPP-to-Grid	Profit Max., Stochastic Receding Horizon Strategy	Battery aging costs, EV owner incentives, energy sales revenue.
[153]	Spot Market, Ancillary Services (Partial)	VPP-to-Grid (Centralized Bidding)	Flexible Bidding (Block/Hourly), Social Welfare Maximization	Flexibility Premium, energy price.

While the aforementioned market strategies define the VPP's economic goals, their realization is contingent upon the accuracy of resource forecasting. Therefore, the following section examines the mathematical frameworks used to model the inherent uncertainties that dictate the success of these market bids.

5. Uncertainty Modeling and Risk Management

The operational success of Virtual Power Plants (VPPs) is intrinsically linked to the robust management of multi-dimensional system uncertainties. These uncertainties, arising from both the supply and demand sides, introduce significant operational risks. Specifically, the weather-dependent intermittency of wind and solar resources often leads to deviations from market commitments, resulting in substantial financial penalties [77,84,144]. Therefore, accurately modeling the spatio-temporal correlation between different renewable sources is essential for precise risk assessment [64,72]. Beyond generation, fluctuations in consumer loads and the stochastic nature of participant responses to Demand Response (DR) incentives introduce additional layers of complexity to VPP flexibility management [84,135,141]. Furthermore, electricity price volatility represents a critical exogenous uncertainty that directly dictates the VPP's profit margins [45,63,154]. In the context of transportation electrification, the uncertain arrival and departure (plug-in/plug-out) times of Electric Vehicles (EVs), coupled with heterogeneous consumer comfort preferences, further complicate the characterization of the "virtual battery" capacity available for grid support [84,107,151,152].

Beyond traditional bi-level or tri-level robust formulations, the recent literature has shifted toward more sophisticated hierarchical structures to manage the high-dimensional uncertainties of massive DER integration. A prominent advancement in this domain is the data-driven quad-level approach, which provides a granular framework for coordinating

hybrid microgrids within a VPP ecosystem [155]. Unlike conventional RO that suffers from excessive conservativeness, these quad-level models incorporate adjustable conservativeness mechanisms. This allow operators to dynamically tune the uncertainty sets based on real-time data distributions, thereby balancing the trade-off between system reliability and operational cost-efficiency. By decomposing the decision-making process into four interactive layers—ranging from strategic scheduling to real-time resource adjustment this approach effectively handles the massive penetration of intermittent renewables while maintaining computational tractability in large-scale hybrid systems [155].

5.1. Mathematical Approaches to Uncertainty

The literature reveals a transition toward increasingly sophisticated mathematical frameworks, categorized based on the nature of the uncertainty and data availability:

- Scenario-Based Stochastic Optimization (SBSO): This approach maximizes expected profit by generating discrete scenarios based on known Probability Density Functions (PDFs) of uncertain variables [68,84].
- Robust Optimization (RO): Unlike SBSO, RO defines an "uncertainty set" rather than a probability distribution. It seeks to produce decisions that remain feasible under the worst-case scenario [115,144]. While highly reliable, this method can sometimes lead to over-conservatism [45,72].
- Hybrid Stochastic-Robust Approaches (SRO): These models balance profitability and security by employing stochastic methods for price uncertainty while applying robust optimization to handle volatile wind generation [156,157].
- Chance-Constrained Programming (CCP): This method ensures that critical operational constraints (e.g., voltage stability or line thermal limits) are satisfied within a predefined confidence level or probability [75,158].
- Conditional Value-at-Risk (CVaR): Derived from financial risk management, CVaR is used to quantify and control tail-end risks (extreme losses) resulting from large real-time deviations [45,103,135].
- Information Gap Decision Theory (IGDT): In environments characterized by severe data scarcity where PDFs are unavailable, IGDT provides a flexible framework, allowing operators to choose between risk-averse (protecting against failure) or opportunity-oriented (capitalizing on favorable winds) strategies [159–161].
- Distributionally Robust Optimization (DRO): Representing the current frontier, DRO synergizes the advantages of both stochastic and robust frameworks. By utilizing data-driven Wasserstein metrics to define an ambiguity set of distributions, it achieves a more balanced management of uncertainty without the heavy computational burden or pessimism of traditional methods [45,72,76].

To enhance the robustness of the decision-making process against distribution modeling errors, Distributionally Robust Optimization (DRO) utilizes an ambiguity set ($\mathcal{P}$) based on the Wasserstein distance:

$$\mathcal{P} = \{\mathbb{P} \in \mathcal{M}(\Xi): \mathbb{W}(\mathbb{P}, \widehat{\mathbb{P}}_N) \leq \epsilon\}$$

Here, $\mathbb{P}$ is the true probability distribution, $\widehat{\mathbb{P}}_N$ is the empirical distribution derived from N historical samples, and $\mathbb{W}(\cdot,\cdot)$ is the Wasserstein metric. The radius ϵ determines the degree of conservativeness, defining a 'ball' of distributions around the empirical data within which the worst-case expectation is minimized.

5.2. Risk Profiles and Decision-Making Behavior

The risk appetite of a VPP operator fundamentally dictates the bidding strategies and operational dispatch decisions. In the literature, these risk profiles are categorized based on their response to market volatility and technical uncertainty:

- Risk-Averse: This profile prioritizes system security and reliability. Under conditions of high uncertainty, risk-averse operators tend to reduce market exposure and maintain higher local reserve capacities to hedge against potential imbalance penalties [135,161,162].
- Profit-Seeker (Opportunistic): This profile views uncertainty as a potential source of revenue. By adopting aggressive bidding strategies, opportunistic operators aim to capitalize on positive deviations such as wind generation exceeding forecasted values to maximize instantaneous profit [60,78,160,161].
- Mean-Deviation Minimization: This approach seeks a middle ground by establishing a trade-off between expected profit and its volatility (variance). The goal is to ensure revenue stability and provide more predictable financial outcomes over long-term operation [117].

5.3. Scenario Management and Computational Efficiency

Managing high-dimensional data and large-scale scenarios requires advanced techniques to maintain computational tractability without sacrificing the accuracy of the model:

- Monte Carlo Simulation (MCS): Serving as a fundamental tool for uncertainty analysis, MCS generates a vast number of stochastic scenarios through random sampling to test system performance under diverse conditions [151].
- Scenario Reduction Strategies: To alleviate the computational burden while maintaining high representative fidelity, thousands of raw scenarios are condensed into a smaller, manageable subset. This is achieved using clustering algorithms such as K-means and K-medoids, or heuristic methods like Fast Forward Selection (FFS) [151,163–165].
- Unscented Transform (UT): For non-linear power system models, UT provides a highly efficient alternative to traditional stochastic methods. It captures the mean and covariance of uncertain variables using a minimal number of sample points (sigma points), significantly accelerating the optimization process compared to MCS [69,154].

5.4. Critical Synthesis: Selection Criteria for Uncertainty Frameworks

The selection of an uncertainty modeling technique involves a fundamental trade-off between computational efficiency and solution conservativeness [166]. While Stochastic Programming (SP) provides a high-fidelity representation of the probability distribution, its reliance on a large number of scenarios makes it computationally prohibitive for real-time VPP dispatch in large-scale networks [167]. In contrast, Robust Optimization (RO) offers superior computational speed by solving a deterministic equivalent; however, its 'worst-case' orientation often leads to overly conservative bids that reduce market competitiveness, a phenomenon widely discussed in recent DER integration studies [168].

Information Gap Decision Theory (IGDT) emerges as a preferred alternative when historical data is scarce or unreliable, as it quantifies the degree of 'robustness' without requiring a formal probability density function [169]. However, for VPPs operating in highly volatile markets, Distributionally Robust Optimization (DRO) is increasingly favored as it bridges the gap between SP and RO. By utilizing ambiguity sets often based on the Wasserstein distance or moment constraints DRO provides a solution that is less

conservative than traditional RO while remaining significantly more robust to distribution modeling errors than pure stochastic approaches [170].

A comparative overview of the primary uncertainty management techniques in VPPs is presented in Table 5. The analysis evaluates each method according to its data requirements, computational cost, degree of conservativeness, and typical application domains. This comparison underscores the balance between computational efficiency and solution robustness, providing a clear rationale for technique selection in varying market and grid conditions.

Table 5. Comparative Analysis of Uncertainty Management Techniques in VPPs [166–171].

Technique	Data Requirement	Computational Cost	Conservativeness	Key Application
Stochastic (SP)	High (Needs PDF)	High (Scale-dependent)	Low	Day-ahead scheduling
Robust (RO)	Low (Uncertainty set)	Low	High	Real-time security
DRO	Medium (Ambiguity set)	Medium/High	Medium	Risk-averse bidding
IGDT	Minimal (Point estimate)	Very Low	Adjustable	Strategic planning
Chance Constrained	High	Medium	Low	Reliability assessment

A systematic review of uncertainty modeling techniques and risk management frameworks in the virtual power planning (VPP) literature is presented in Table 6.

Table 6. Systematic review of uncertainty modeling techniques and risk management frameworks in VPP literature.

Reference	Sources of Uncertainty	Optimization Methodology	Risk Profiles and Attitudes	Scenario Management and Characterization
[45]	Market price, wind power forecasting error.	Distributionally Robust Optimization (DRO) via Wasserstein Metric.	Risk-Averse (CVaR).	Data-driven, Wasserstein Ball (Ambiguity Set).
[63]	Wind, solar, load, market price.	P-Robust Stochastic Programming, Fuzzy Satisfaction Method.	Minimax Regret, Profit-Risk balance.	Probability Density Functions (PDFs), MILP-based scenario reduction.
[68]	RES generation deviations (unit outages/curtailment), price volatility.	Two-stage Scenario-Based Stochastic Optimization (SBSO), CVaR.	Comparative analysis: Risk-Averse vs. Risk-Neutral.	Scenario generation based on failure type and duration.
[72]	Correlated wind and PV generation.	Two-stage Distributionally Robust Optimization (DRO).	Risk-Averse (Ambiguity Set).	Scenario generation via Copula functions.
[75]	Wind, solar, load, line contingencies.	Chance-Constrained Programming (CCP).	Reliability Level (ϵ)-Risk-Averse.	Probability distributions (Weibull, Normal).
[76]	Wind, PV, EV responsiveness.	Distributionally Robust Optimization (DRO)-Wasserstein.	Risk-Averse (Worst-case distribution).	Data-driven ambiguity sets.
[78]	Wind, EV behavior, price volatility.	Hybrid Stochastic/Robust Optimization.	Risk-Averse (RA) and Profit-Seeker (PS).	Box and Budget sets for wind; Scenarios for price and EV.
[84]	RES generation deviations (wind), load demand.	Scenario-Based Stochastic Optimization (SBSO).	Risk-neutral focus (Expected Value).	Monte Carlo Simulation, SCENRED (Scenario reduction).

[103]	Wind, solar, load.	Stochastic Game Theory.	Risk-Averse (CVaR).	Stochastic scenario modeling.
[135]	Wind, price, load, and contingencies (N-1).	Two-stage Stochastic Programming.	Risk-Averse (CVaR).	Monte Carlo Simulation, K-means clustering.
[107]	Competitor VPP prices, EV behavior, wind.	Bi-level Stochastic Programming.	Risk-Averse (CVaR).	PDF modeling, Monte Carlo, K-means reduction.
[117]	Market price volatility, wind generation.	Stochastic Optimization with Dominance Constraints (FODC/SODC).	Risk-Averse (Tail Risk control), Mean-Deviation Minimization.	ARIMA for generation + Scenario reduction.
[151]	PV errors, EV charging demand.	Two-stage Stochastic Programming.	Expected Cost (Risk-Neutral).	Monte Carlo Simulation, K-means clustering.
[152]	EV user behavior (battery availability), wind deviations, market price.	Stochastic Receding-Horizon Convex Optimization.	Profit-Seeker: Revenue maximization under uncertainty.	AI-driven forecasting: Mixture Density Neural Networks (MDNN).
[154]	Active/Reactive load, price, RES generation.	Bi-level Optimization.	Flexibility Tolerance (ΔF).	Unscented Transform (UT).
[158]	PV and load forecasting errors, price.	Stochastic MPC, Chance-Constrained (CC).	Pessimistic/Optimistic forecast management.	Historical error distributions (CDF/ECDF).
[160]	Market price volatility, RES deviations (PV/wind), load demand.	Information Gap Decision Theory (IGDT) for price; Cornish-Fisher VaR for Load/RES.	Robustness Strategy (Risk-Averse) vs. Opportunity Strategy (Risk-Seeking).	Statistical distribution estimation via historical data analysis.
[163]	Wind, PV, price, load, EV user behavior.	Point Estimation Method (PEM).	Hedging through reserve capacity.	Statistical Moments (Deterministic equivalence).
[172]	Wind and solar forecasting errors.	Quantile and Superquantile Theory.	Tail Risk (CVaR equivalent).	Forecasting via Artificial Neural Networks (ANN).

Modeling uncertainty provides a secure bidding range; however, economic optimization alone does not guarantee physical feasibility. The next section transitions from financial scheduling to the technical control architectures required to enforce real-time network constraints.

6. VPP Architecture and Control Schemes

The methodological core of the Virtual Power Plant (VPP) paradigm is constructed upon hierarchical decision-making structures, diverse control architectures, and sophisticated optimization techniques. These frameworks enable the VPP to navigate the complexities of market interactions while maintaining high-fidelity internal resource management.

6.1. Optimization Frameworks and Decision Hierarchies

VPP operations are formulated through different optimization layers based on the complexity of the interaction between stakeholders:

- Single-Level Optimization: These are often linear or convex formulations where complex hierarchical problems, such as Mathematical Programs with Equilibrium

Constraints (MPEC), are transformed into a single-level equivalent. This is typically achieved by leveraging Karush-Kuhn-Tucker (KKT) conditions and the Strong Duality theorem to ensure solvability [110,122,147,154].

- Bi-Level Optimization: Specifically utilized to model the strategic interaction between the VPP and upper-level entities (DSO/TSO) or between the VPP and its internal assets [107,110,122,154]. The most prevalent framework is the Stackelberg Game (Leader-Follower) model, where a "Leader" (e.g., the VPP operator) dictates price or dispatch strategies, and the "Followers" (e.g., individual DERs) respond optimally to these signals [8,119,147,148,173–175].
- Multi-Stage Frameworks: These structures extend decision-making across various temporal horizons, typically encompassing day-ahead, intraday, and real-time scheduling [84,91,176–178]. This temporal decomposition allows for the progressive correction of forecasting errors as more accurate data becomes available closer to the dispatch hour [65,179].

6.2. Control Mechanisms and Algorithmic Solutions

The technical operation of VPPs relies on the selected control topology, each presenting a distinct trade-off between optimality and data privacy:

- Centralized Energy Management Systems (CEMS): In this configuration, all telemetry data from DERs are aggregated at a single control center for global optimization. While ensuring a theoretical global optimum, it faces significant computational intractability in large-scale systems and poses substantial data privacy risks [18,145,180–182].
- Distributed Control: To preserve privacy and enhance scalability, distributed architectures allow individual DERs or sub-clusters to make autonomous decisions. Communication is limited to neighboring nodes through algorithms such as the Alternating Direction Method of Multipliers (ADMM) or consensus-based protocols [34,36,55,92,181,183–185].
- Iterative Solution Techniques: Advanced decomposition methods are frequently employed to handle large-scale or robust problems. Key techniques include Column-and-Constraint Generation (C&CG) widely used to accelerate robust optimization [95,156,186–188] and Benders Decomposition (BD), which partitions complex master problems into more manageable sub-problems [183,189–191]. Contemporary research is increasingly moving toward Hybrid (Centralized-Distributed) architectures and Centralized Distributed Control (CDC) topologies. These emerging structures aim to bridge the gap between the efficiency of centralized schemes and the resilience of distributed systems, specifically targeting enhanced robustness against cyber–physical attacks [181,182].

A comparative analysis of control architectures in virtual power plant management is presented in Table 7.

Table 7. Comparative analysis of control architectures in Virtual Power Plant management [181,182,190].

Feature	Centralized Control	Distributed Control
Computational Overhead	High; becomes intractable as the number of DERs increases.	Low; the computational burden is distributed across local units.
Data Privacy	Poor; necessitates the flow of all raw data to the central hub.	Robust; only boundary variables or limited information are shared.

Reliability	Low; susceptible to critical risks from a single point of failure.	High; resilient to cyber-attacks and communication link failures.
Decision Speed	May exhibit significant latency in large-scale systems.	Significantly faster due to plug-and-play capabilities.
Optimality	Global optimum can be theoretically guaranteed.	Converges toward the global optimum if properly formulated.

6.3. Flexibility and Capacity Modeling

Flexibility and capacity modeling constitutes the process of determining the technical boundaries within which a VPP can provide services to the grid.

- VPP Capability Curve (VPP-CC) and Feasible Operating Region: These represent the geometric characterization of the active (P) and reactive (Q) power limits that a VPP can sustain without violating internal network constraints, such as voltage limits and thermal line ratings [19,22,192–194]. The technical flexibility of inverter-based resources within a VPP is constrained by their P-Q capability curve, which defines the limits of active (P) and reactive (Q) power delivery based on the inverter's apparent power rating (S_{max}):

$$P_{i,t}^2 + Q_{i,t}^2 \leq (S_{i,max})^2$$

Additionally, minimum and maximum voltage limits ($V_{min} \leq V_{n,t} \leq V_{max}$) and thermal line capacities ($|I_{l,t}| \leq I_{l,max}$) serve as non-convex constraints that must be satisfied to ensure grid security during VPP dispatch.

- Robust Capability Curve (RCC): This defines a guaranteed operational envelope, ensuring that the VPP can fulfill its market commitments even under significant system uncertainties [192].
- Aggregate Flexibility Assessment: This framework models the collective flexibility of distributed assets (e.g., BESS, PHS, and DR) through equivalent Virtual Generator (VG) or Virtual Battery (VB) parameters, simplifying the interaction with system operators [23,195].

A critical bottleneck in real-time VPP operations is the conflict between the non-convexity of physical grid constraints and the requirement for ultra-low latency (<1 ms) in frequency regulation services. While convex relaxation techniques, such as Second-Order Cone Programming (SOCP), significantly improve computational tractability for day-ahead or intra-day scheduling, they often fall short of the sub-millisecond response times necessitated by primary frequency control [196]. To bridge this gap, emerging control architectures are moving toward 'Neural-OPF' frameworks, where deep neural networks are trained to approximate the AC-OPF solutions. By offloading the heavy computational burden to an offline training phase, these AI-driven surrogates can provide near-instantaneous, physics-informed control signals during real-time contingencies. Additionally, the integration of edge computing at the DER level is being explored to decentralize the decision-making process, thereby bypassing the communication delays inherent in centralized SCADA-based architectures and ensuring grid stability during rapid frequency deviations [197].

6.4. Artificial Intelligence and Machine Learning Integration

Artificial Intelligence (AI) and learning-based techniques are increasingly deployed in non-linear and stochastic environments where traditional mathematical models, such as Mixed-Integer Linear Programming (MILP), face scalability or modeling limitations.

- Deep Reinforcement Learning (DRL): To address complex scheduling and control problems in a model-free manner, advanced DRL algorithms including Soft Actor-Critic (SAC), Deep Deterministic Policy Gradient (DDPG), and Twin Delayed DDPG (TD3) are utilized. These agents learn optimal policies through continuous interaction with the environment [46,141,185,198–200].
- Generative Adversarial Networks (GAN): These architectures are primarily employed for generating high-fidelity renewable energy production scenarios and facilitating data augmentation, which is critical for training robust models with limited historical datasets [164,201].
- Advanced Forecasting Architectures: Deep learning models, such as Graph Convolutional Networks (GCN), Bidirectional Long Short-Term Memory (BiLSTM), and Informers, are leveraged to enhance the spatio-temporal accuracy of generation and market price predictions, thereby reducing the VPP's exposure to imbalance risks [93,140,202–204].

Despite the high performance of Deep Reinforcement Learning (DRL) in simulation environments, its practical maturity for real-time VPP control remains limited by 'black-box' interpretability issues and the lack of formal stability guarantees. In contrast, hybrid models that combine AI-based forecasting with traditional MILP-based optimization currently offer the most reliable path for commercial deployment, balancing innovation with operational safety.

Despite the success of traditional generative frameworks like GANs, their performance significantly deteriorates under data-scarce or cold-start conditions scenarios common in newly commissioned wind or solar farms where historical datasets are insufficient for training deep architectures [205]. To overcome these limitations, the literature is pivoting toward Diffusion Models, which offer superior stability and high-fidelity time-series synthesis by learning to reverse a multi-step noise addition process [206]. Unlike GANs, which often suffer from mode collapse, diffusion-based architectures can reconstruct the underlying probability distribution of intermittent RES generation even with sparse initial data, providing a robust tool for scenario generation.

Furthermore, the emergence of Kolmogorov-Arnold Networks (KAN) represents a paradigm shift in VPP modeling [207]. By replacing fixed activation functions on neurons with learnable functions on edges, KANs provide higher accuracy in approximating the non-linear dynamics of power systems with fewer parameters compared to traditional Multi-Layer Perceptrons (MLPs). This structural efficiency and the inherent spline-based interpretability make KANs particularly effective for cold-start forecasting, where rapid convergence is critical for maintaining the stability of the VPP's energy management system [207].

The categorization of VPP control architectures, optimization hierarchies, and AI integration strategies is presented in Table 8.

Table 8. Categorization of VPP control architectures, optimization hierarchies, and AI integration strategies.

Reference	Optimization Hierarchy	Control & Solution Mechanisms	Flexibility & Capacity Characterization	AI and Machine Learning Integration
[22]	Dynamic Partitioning	Distributed Control	SoC Balancing Capacity	PageRank (Graph Theory), DBSCAN (Clustering)
[23]	Bi-Level Logic (used for grid constraint decomposition)	Iterative Boundary Diminishment (to find Inscribed Polytopes)	Aggregate Flexibility: Projection of high-dimensional regions onto Virtual Generator (VG)	Gaussian Mixture Model (GMM): Stochastic modeling of RES forecasting errors.

			and Virtual Battery (VB) parameters.	
[36]	Decomposition-Coordination	Distributed Control: Asynchronous Hybrid ADMM	Comfort Flexibility: User preference deviation tolerance	ARIMA: Time-series analysis for missing data imputation
[46]	Two-Level (Master-Slave)	Hierarchical Planning, Kriging Meta-model	Power Output Limits	Genetic Algorithm (GA)
[91]	Single-Level (Multi-objective)	Centralized Control (Multi-Area Coordination)	Flexible and Spinning Reserve (EV, ESS)	Marine Predators Algorithm (MPOA) (Swarm Intelligence)
[93]	Single-Level (MILP)	Centralized Control	Flexible Reserve (EV, ESS)	BiLSTM (Wind/Price/Load Forecasting), Rough ANN (EV Behavior Prediction)
[107]	Bi-Level (Reduced to Single-Level via KKT)	Centralized (Competitive Bidding)	Self-Sufficiency Factor (SSF), EV Battery Capacity	K-means (Scenario Reduction)
[122]	Bi-Level (Reduced to Single-Level via KKT Conditions)	Centralized (Market Clearing Simulation)	Load Shedding Capacity	Discrete Water Flow Algorithm (DWFA) (Meta-heuristic), Chaos Theory
[140]	Multi-Stage (DA/RT via Rolling Horizon)	Centralized VPP Operator	Flexibility Modeling based on Customer Bid Data	Hybrid Deep Learning: (BiLSTM, TCN, EMD) and Unsupervised Learning: Customer Clustering
[156]	Two-Stage (Min-Max-Min Structure)	Iterative Solution: TC&CG Algorithm (Benders-like)	CHP and CPP Reserve Capacities	Dirichlet Process Mixture Model (DPMM) for uncertainty sets
[173]	Bi-Level (Master-Slave/Leader-Follower)	Centralized Pricing, Distributed Investment Decision	Capacity Utilization Constraints	Grey Wolf Optimizer (GWO)
[176]	Bi-Level (KKT Reduction), Multi-Stage Quasi-Predictability	Centralized Control	3-Period VPP Model (Constraint tightening for generators)	Random Forest (for forecasting)
[177]	Multi-Stage (Day-Ahead, Real-Time, Balancing)	Centralized Control (VPP Control Center)	EV Charge/Discharge Capacity and Load Shifting	Improved Artificial Bee Colony (IABC) (Heuristic)
[179]	Two-Stage Stochastic (Day-Ahead/Intraday)	Centralized Control (Dynamic Allocation)	Energy-Constrained Resource Modeling	Bidirectional LSTM (BiLSTM) Forecasting
[181]	Structural Optimization (Partitioning)	Network Embedding, Centralized Control Point (CCC) Selection	Communication Capability Matrix	Graph Representation Learning: Node2vec, Clustering: K-means
[182]	Single-Level (ITAE minimization for PI gain tuning)	Hybrid (Centralized + Local): Centralized Active Power; Local SPQ Droop control for Reactive Power	Dynamic Response Time: Modeled based on asset time constants (τ) (e.g., Fast ESS vs. Slow MTG)	Particle Swarm Optimization (PSO) for controller parameter tuning
[184]	Distributed Optimization (Dual Decomposition)	Distributed Control (Dual Consensus-RFDCA)	Load Shedding Capacity	Iterative Convergence analysis

[192]	Multi-Stage (Reduced to COCP via ADP)	Centralized Control: Auto-Tuned Policy	Signal Tracking Flexibility: Ramp rates and tracking error bounds	Auto-Tuning: Learning parameters via Implicit Differentiation
[194]	Single-Level (Time-Decoupled)	Distributed Optimization (ADMM)	Spinning Reserve and Dynamic Boundary Setting	Hybrid Strategy HSPSO
[195]	Single-Level	Non-iterative TSO Coordination	Stochastic Power Flexibility Region (PFR)/P-Q Polygon, Temporally Coupled Flexibility (TCF)	Data-driven: Convex Piecewise-Linear Fitting, Gaussian Mixture Model (GMM)
[201]	Single-Level (Robust Optimization)	Centralized Training	Robustness against corner-case scenarios	Generative Adversarial Networks (GAN), DRL (DDPG)

7. Distribution Grid Integration and Operational Constraints

In the process of grid integration, Virtual Power Plants (VPPs) are managed not merely as economic portfolios but as technical entities subject to rigorous physical constraints. To analyze the impact of VPPs on the physical grid and to offer secure capacity to transmission and distribution systems, various mathematical formulations are employed.

7.1. Power Flow Modeling and Benchmark Systems

To ensure the physical feasibility of VPP dispatch, full AC Optimal Power Flow (AC-OPF) models are utilized, incorporating voltage limits and reactive power balances [20,65]. To address the non-convexity and high computational complexity of these models, relaxation and approximation methods such as Linearized AC (LAC-OPF) or Second-Order Cone Programming (SOCP) are preferred [154,160]. For radial distribution networks, Linearized DistFlow models are the standard for calculating the relationship between voltage profiles and power flow [22]. Recent advancements include "Enhanced Lin-DistFlow" models developed specifically to minimize approximation errors in unbalanced grid structures [208]. The accuracy of VPP algorithms is validated using standardized grid topologies. The IEEE 33-bus [13,209], and IEEE 69-bus [69,210] systems remain the most prevalent benchmarks for distribution-level VPP research.

7.2. Technical Constraints for Grid Security

VPP optimization is conducted under a set of constraints that protect both the internal limits of the assets and the security of the external network:

- Voltage Security and Regulation: Maintaining grid stability and avoiding violations of physical limits are among the most critical tasks in power system operation. To mitigate overvoltage and undervoltage conditions, voltage stability metrics, such as the Voltage Security Index (VSI), are incorporated into the optimization objective function [211,212].
- Active and Reactive Power Balance: The operational boundaries at the Point of Common Coupling (PCC) are defined through P-Q Feasible Regions, which characterize the interaction between active (P) and reactive (Q) power [19,20].
- Thermal Line Limits and Congestion: Constraints are imposed to ensure transmission lines do not exceed their thermal capacity [122,213]. The deployment of Dynamic Line Rating (DLR) technology allows these limits to be expanded dynamically based on ambient weather conditions [24,25].

- Generator Ramping Limits: These define the maximum rate at which controllable units (e.g., gas turbines) can adjust their power output between consecutive time intervals, a critical factor for real-time balancing [186].

7.3. DSO Coordination and Market Integration

Coordination with the Distribution System Operator (DSO) relies on both economic and technical data exchange:

- Distribution Locational Marginal Pricing (DLMP): This dynamic pricing mechanism reflects the marginal cost of congestion and network losses at each node [214]. VPPs optimize their schedules based on these local price signals to reduce overall system costs [215].
- Distribution Space Constraint (DSC) Uncertainty: This refers to the ambiguity in the capacity limits provided to the VPP by the DSO for security reasons. VPP operators can take an "active" role by utilizing machine learning to predict these conservative limits, thereby maximizing profit potential without compromising security [216].

7.4. Ancillary Services and Grid Resilience

VPPs contribute to grid stability through various support services:

- Volt/VAR Control (VVC): By leveraging the reactive power capabilities of multiple VPPs, grid voltage can be regulated efficiently. This is often achieved via model-free and distributed algorithms like ADMM to maintain data privacy [217].
- Network Reconfiguration: Optimizing the grid topology by changing the status of switches. This dynamic boundary adjustment can reduce voltage deviations by up to 48% [218].
- System Resilience and Self-Healing: During natural disasters or cyber-attacks, VPPs enhance resilience by partitioning the grid into autonomous, self-sufficient microgrids [37]. Such self-healing capabilities can reduce load shedding costs often measured as Value of Lost Load (VOLL) by up to 93% [67].

The technical synthesis of grid integration, operational constraints, and distribution system operator/virtual power plant coordination is presented in Table 9.

Table 9. Technical synthesis of grid integration, operational constraints, and DSO/VPP coordination.

Reference	Grid Models and Topologies	Operational Constraints	DSO/DISCO Interaction	Flexibility and Grid Services
[13]	IEEE 33-Bus System, AC-OPF based on SOCR-BFM (Second-Order Cone Relaxation-Branch Flow Model).	Voltage limits (0.95–1.05 p.u.), line current limits, network losses, power balance.	VPP-DSO partnership aimed at peak-to-valley load difference minimization.	System reliability indices (LOLP, EENS), dynamic risk reserve.
[19]	IEEE 33-Bus and IEEE 123-Bus systems, Linearized Network Configuration.	Line and transformer capacities (Sij limits), voltage limits (Vmin,Vmax), power factor (DER limits).	TSO-DSO Interface: VPP presents a secure operating region (P-Q Curve) compliant with grid constraints.	P-Q Capability Curve (VPP-CC): Geometric representation of total flexibility.
[22]	IEEE 33-Bus, IEEE 136-Bus, DistFlow model.	AC feasibility, voltage and current constraints.	TSO-VPP interaction (Capacity region presentation).	Power Transfer Region characterization.

[25]	AC-OPF Constraints, IEEE 33-Bus and IEEE 123-Bus systems.	Line ampacity (Dynamic via DLR), voltage limits.	DSO leverages DLR to relax grid constraints and provide expanded flexibility to the TSO.	Expansion of the VPP Flexibility Region (P-Q).
[65]	HL: Linearized Power Flow; ML/LL: Second-Order Cone (SOC) Relaxation (South Australian Grid).	Nodal voltage limits (0.95–1.05 p.u.), line thermal capacities, On-Load Tap Changer (OLTC) positions.	VPP assuming DSO roles or providing contractual support to the DSO.	Voltage support, synthetic inertia, Fast Frequency Response (FFR).
[67]	IEEE 13 and 123 Node Systems, Unbalanced Power Flow.	Current Unbalance Factor (CUF), thermal limits, radial topology.	Dynamic Operating Envelopes (DOEs) (VPP export limits).	Grid partitioning, system resilience.
[122]	IEEE 24-Bus and 6-Bus systems, DC Optimal Power Flow (DC-OPF).	Line capacity limits (Congestion management), power balance.	Network congestion management.	Congestion mitigation via Interruptible Load (IL).
[154]	IEEE 69-Bus, Linearized AC-OPF (LAC-OPF).	Voltage deviation, line capacity, transformer capacity, VPP flexibility boundaries.	Bi-level optimization between ADN Operator and VPP.	Active and Reactive power support.
[186]	IEEE 33-Bus, 185-Bus, Linear Power Flow (LPF).	Nodal voltage, line current, PCC power balance.	TSO-DSO/VPP coordination (Dispatch instructions).	TSO instruction tracking, ramping flexibility.
[208]	Unbalanced Distribution Grid, Enhanced LinDistFlow, IEEE 13 & 123 Bus.	3-phase power balance, bus voltage limits, line current limits.	Bi-level DSO-VPPO interaction (Security control).	Dynamic balancing through P2P trading.
[213]	35-Bus Distribution System, Linearized AC-OPF.	Line capacity (Smax), voltage limits (0.9–1.1 p.u.).	Regulation signal security check.	Frequency regulation.
[210]	Dynamic OPF; Multi-Area (IEEE 33, 15, 69 Bus systems).	Power balance (equality), voltage and line flow limits (inequality), generator ramp rates.	Multi-operator VPP interaction via tie-lines.	Inter-VPP power trading, Demand Side Management (DSM).

7.5. Global VPP Case Studies and Commercial Deployments

To bridge the gap between theoretical research and industrial practice, it is essential to examine established commercial VPP platforms that have successfully integrated distributed assets into wholesale markets. Table 10 summarizes major global VPP deployments, categorizing them by their Technology Readiness Level (TRL), geographic footprint, and primary service offerings.

For instance, Next Kraftwerke in Germany represents one of the most mature VPP architectures, aggregating over 15,000 units to provide secondary and tertiary frequency regulation. Meanwhile, Tesla's South Australian VPP demonstrates the efficacy of large-scale residential battery aggregation for grid support. These real-world deployments highlight that while frequency regulation and peak shaving are currently the most common services, the transition toward multi-market participation (energy, ancillary, and capacity markets) is the next frontier for commercial viability [219,220].

Table 10. Systematic Overview of Leading Global VPP Projects.

Project/Platform	Region	Primary Assets	Primary Services	Technology Readiness Level (TRL)
Next Kraftwerke	Europe (DE, BE)	Biogas, Solar, Wind	Frequency Regulation, Trading	9
Tesla SA VPP	Australia	Residential BESS, PV	Peak Shaving, V2G Support	8–9
Statkraft VPP	Europe (UK, DE)	Wind, Hydro, Solar	Market Access, Intermittency Management	9
StoreNet	Ireland	Residential BESS	Local Grid Balancing	7
Enel X VPP	North America	Industrial DR, BESS	Capacity Market, Peak Shaving	9

8. Challenges and Future Directions

Scholarly discourse surrounding Virtual Power Plants (VPPs) highlights a critical duality between inherent operational hurdles and the strategic evolutionary paths of the technology. As the density of integrated Distributed Energy Resources (DERs) scales, the computational complexity of bi-level and Mixed-Integer Non-Linear Programming (MINLP) formulations grows exponentially [31,176]. This "curse of dimensionality" poses a significant barrier to real-time applications, such as sub-second frequency regulation services, where low-latency decision-making is mandatory [43,221]. Data privacy remains a critical concern within centralized management frameworks. The necessity of sharing granular telemetry data including prosumer load profiles and precise geographical coordinates creates substantial privacy risks [222,223]. Furthermore, the heavy reliance of VPPs on Information and Communication Technology (ICT) infrastructures expands their vulnerability surface to sophisticated cyber–physical threats, most notably False Data Injection (FDI) and Denial of Service (DoS) attacks [37,224]. From a stochastic perspective, the intermittency of renewable generation, coupled with market price volatility and the non-deterministic behavior of Electric Vehicle (EV) users, continues to complicate uncertainty management. These factors frequently lead to significant deviations from market commitments, thereby incurring heavy imbalance penalties [68,158]. Moreover, a prevalent trend in the literature involves the over-simplification or omission of physical grid constraints (e.g., full AC-OPF and nodal voltage limits) to maintain computational tractability. Such idealized approximations risk generating solutions that are mathematically optimal but physically infeasible in real-world deployment [22,113,154]. An overview of the technical and operational challenges in Virtual Power Plant ecosystems is shown in Figure 6.

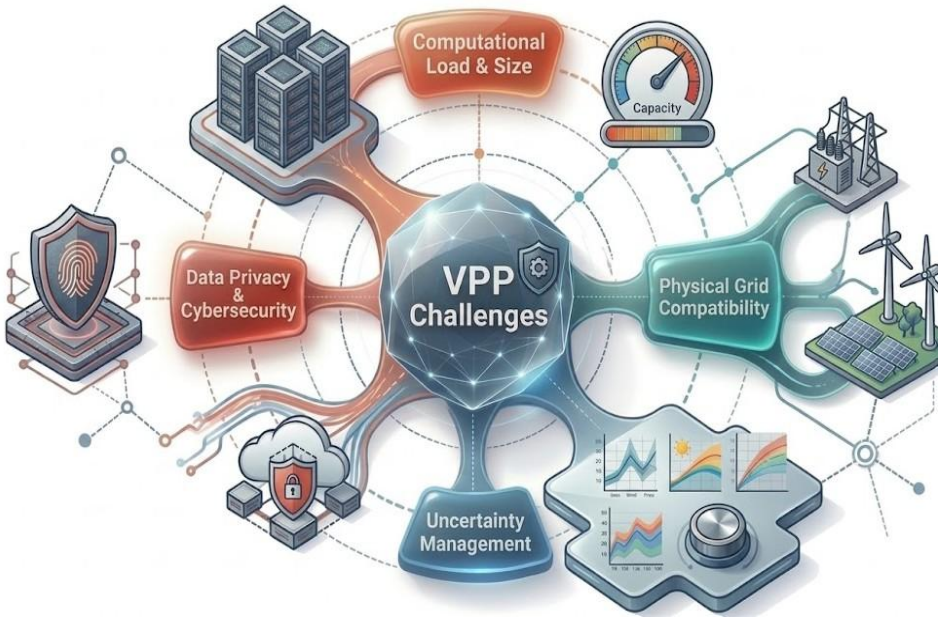

Figure 6. Overview of technical and operational challenges in Virtual Power Plant ecosystems.

Current scholarly trends indicate a significant methodological shift in the optimization and management of Virtual Power Plants (VPPs). There is a prominent transition from traditional stochastic programming toward Distributionally Robust Optimization (DRO) which is inherently less sensitive to distribution modeling errors and deep learning-enhanced hybrid frameworks (e.g., GAN, BiLSTM, DRL) [93,225,226]. Specifically, the deployment of Deep Reinforcement Learning (DRL) algorithms, such as Soft Actor-Critic (SAC) or TD3, is expected to become the gold standard for solving complex scheduling problems in a model-free and high-dimensional manner [46,141,227].

- Multi-Energy VPPs (MEVPP) and Sector Coupling: Beyond the electrical domain, the emergence of MEVPPs that integrate heat, natural gas, and green hydrogen markets is gaining traction [94,228]. Through strategic sector coupling, these frameworks aim to reduce renewable energy curtailment to near-zero levels by converting surplus electricity into thermal or gaseous energy carriers [94].
- Decentralization and Blockchain: To address data privacy concerns, there is a clear trajectory away from centralized control toward Peer-to-Peer (P2P) trading and distributed algorithms like ADMM [50,103,229,230]. Blockchain technology is anticipated to provide the necessary transparent and secure settlement infrastructure for these decentralized exchanges [61,231].
- Environmental Stewardship and "Dual-Carbon" Goals: The integration of carbon emission allowances (CEA), certified emission reductions (CCER), and Green Certificate mechanisms into VPP objective functions is transforming these entities from purely economic players into critical environmental actors [109,123,232].
- Resilience and Self-Healing: Research is intensifying on the ability of VPPs to maintain grid continuity during natural disasters or cyber–physical contingencies through self-healing mechanisms and grid-forming controllers, effectively partitioning the grid into autonomous, self-sufficient microgrids [37,67,233,234].
- Behavioral Modeling and Prospect Theory: Incorporating Prospect Theory and evolutionary game theory to model the "irrational" or stochastic responses of prosumers to price signals will make demand-side management (DSM) significantly more realistic and robust [138,141,235].
- Spatial-Temporal Complexity of Coupled Transportation-Power Networks: While VPPs effectively utilize Electric Vehicles (EVs) as Virtual Energy Storage (VES),

future architectures must move beyond stationary modeling to address the spatial-temporal complexities of coupled microgrid-transportation networks [236]. The robust scheduling of such systems is non-trivial, as it requires the simultaneous optimization of power flow and traffic flow. Factors such as charging station congestion, dynamic routing, and the stochastic nature of EV arrival/departure times introduce high-dimensional constraints [237]. Future VPP research should focus on co-optimization frameworks that can synchronize the charging requirements of mobile fleets with the localized capacity limits of microgrids, ensuring that V2G support does not compromise urban mobility or distribution transformer longevity [238].

- Security and Reliability-EV Charging Anomaly Detection: As the penetration of V2G-enabled EVs grows, the VPP's reliability becomes increasingly susceptible to cyber–physical threats. A critical research frontier is the development of anomaly detection mechanisms tailored for EV charging behaviors [239]. Malicious actors could potentially trigger False Data Injection (FDI) attacks or manipulate charging signals to create synchronized load spikes, leading to grid instability or battery degradation [240]. Implementing AI-driven diagnostic tools—such as Autoencoders or Graph Neural Networks—to detect deviations from normal charging patterns in real-time is essential for securing the VPP's operational integrity and protecting the infrastructure against both hardware malfunctions and cyber-attacks [241].
- Regulatory Landscapes and Legislative Barriers: Despite the technological maturity of VPP frameworks, their large-scale deployment is heavily dictated by regional regulatory landscapes. In the United States, FERC Order 2222 marks a significant milestone by mandating regional transmission organizations to allow DER aggregations to participate directly in wholesale energy markets, effectively lowering entry barriers for VPPs [242,243]. Similarly, the European Union's 'Clean Energy for All Europeans' Package promotes the concept of 'Citizen Energy Communities,' granting prosumers the legal right to engage in collective energy actions and Peer-to-Peer (P2P) trading [244]. However, significant legislative hurdles remain. Many jurisdictions still struggle with 'double-charging' of network fees for storage-backed VPPs and a lack of standardized tariff structures for cross-boundary energy sharing. Furthermore, the transition of VPPs from passive price-takers to active market participants requires a fundamental redesign of ancillary service protocols to accommodate the stochastic nature of aggregated DERs. Addressing these regulatory inconsistencies is as vital as solving technical non-convexities for the practical realization of the energy transition [245].
- LLM-based Bidding Behavior and Market Sentiment Agents: As electricity markets become increasingly volatile, traditional numerical forecasting models are being augmented with Large Language Models (LLMs) to capture unstructured data such as market sentiment and regulatory news. Emerging research suggests that LLM-based agents can act as 'Market Sentiment Agents' and 'Bidding Behavior Agents,' analyzing textual information from policy reports and news cycles to predict the strategic moves of competitors [246]. By integrating LLMs with traditional deep learning models (e.g., LSTM or Transformers), VPPs can achieve a more holistic price forecasting framework that accounts for both quantitative trends and qualitative market shifts. This intersection of natural language processing and power economics represents a significant frontier for enhancing the bidding accuracy and strategic positioning of VPPs in complex multi-energy markets.

The VPP of the future will transcend being a mere energy aggregator; it will evolve into a "Smart Operating System of Energy" an autonomous entity capable of managing carbon quotas, defending itself against sophisticated cyber-attacks, and orchestrating

decentralized energy exchanges within local communities. Future trends and directions for virtual power plants are summarized in Figure 7.

Figure 7. Future directions and trends for Virtual Power Plants.

9. Conclusions

Virtual Power Plants (VPPs) serve as a critical bridge in the transition of modern energy systems toward a decentralized, flexible, and sustainable architecture. Based on the comprehensive literature review and technical assessments conducted in this study, the following core conclusions are established:

- Integrated Management and System Flexibility: VPPs successfully synchronize intermittent renewables such as wind and solar with flexible assets, including battery storage and thermal loads (HVAC, water heaters). By orchestrating these components, VPPs effectively transform individual resource vulnerabilities into collective systemic strength [31,62,135]. Specifically, the seamless integration of Demand Response (DR) and Electric Vehicles (EVs) has demonstrated the potential to reduce grid imbalance costs by over 80% [151].
- Market Transformation and Economic Efficiency: VPP technology democratizes energy landscapes by enabling small-scale prosumers to participate in wholesale and ancillary service markets, thereby enhancing aggregate social welfare [81,116]. The transition from passive "price-taker" models to strategic "price-maker" frameworks has been shown to augment operational profit margins by 20% to 36% [48,110].
- Methodological Evolution and Artificial Intelligence: Traditional stochastic approaches are increasingly being superseded by Distributionally Robust Optimization (DRO) which offers superior resilience against distribution modeling errors and Deep Reinforcement Learning (DRL), providing model-free solutions for high-dimensional, non-linear dispatch problems [45,200]. These advanced techniques can enhance system reliability under uncertainty by up to 85% [45].
- Sector Coupling and Decarbonization: VPPs are evolving beyond electricity-centric paradigms toward Multi-Energy VPP (MEVPP) structures, integrating thermal, natural gas, and green hydrogen markets [64,88,94]. The integration of carbon trading mechanisms within optimization frameworks has been proven to reduce emissions by 38.9% while significantly incentivizing the penetration of renewable energy [64,123].

- Security and Resilience: VPPs bolster grid resilience during cyber-attacks or natural disasters through self-healing capabilities and autonomous partitioning into microgrids [147]. Furthermore, the adoption of Peer-to-Peer (P2P) trading and distributed control mechanisms (e.g., ADMM) effectively alleviates the computational burden on central authorities while ensuring maximum data privacy for all participants [55,190,222].

The technological ecosystem associated with Virtual Power Plants (VPPs) is visually summarized in Figure 8.

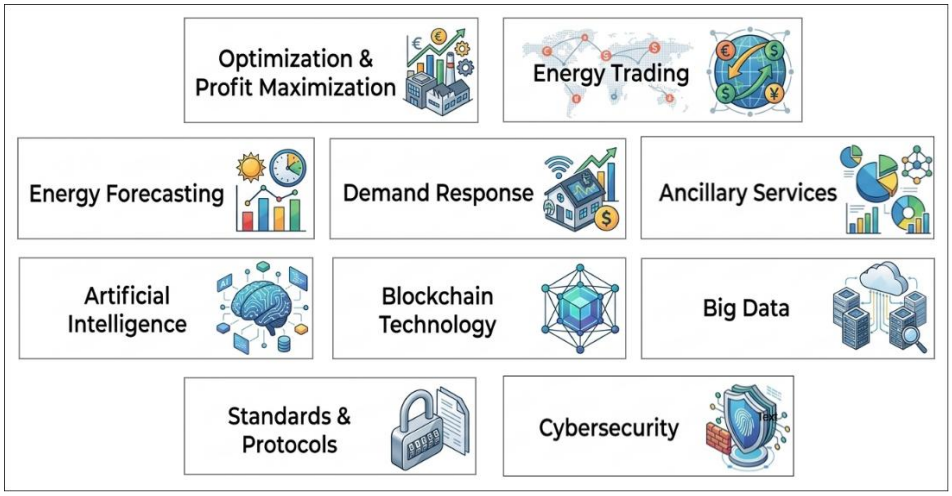

Figure 8. Technological ecosystem associated with Virtual Power Plants (VPP) [247].

In essence, Virtual Power Plants (VPPs) transcend the role of a mere aggregation model; they constitute the smart operating system of a low-carbon economy. The future significance of VPPs in the energy ecosystem is poised to deepen through the integration of blockchain-enabled transparent trading platforms and dynamic pricing models that incorporate behavioral economics and consumer psychology [54,138,159,231].

Despite over a decade of successful pilot projects demonstrating both technical and economic viability, VPPs remain significantly under-recognized by policymakers, utility companies, and the broader consumer base. To unlock their full potential, a coordinated evolution is required in market design, regulatory frameworks, and consumer literacy. The global energy landscape is currently at a critical inflection point. Driven by declining technology costs and emerging fiscal incentives, the adoption of electric vehicles (EVs), residential battery storage, smart thermostats, and other "connected" devices will accelerate exponentially over the next decade. This proliferation provides a massive growth vector for the VPP market [248]. While challenges regarding technical standardization, market rule adaptation, and regulatory barriers persist, these are far from insurmountable when weighed against the immense systemic benefits. Ultimately, VPPs represent more than a technology; they are a paradigm shift that empowers consumers to transition from passive end-users to active stakeholders in the energy solution. This technology holds the potential to build a cheaper, cleaner, and more resilient energy future for all. The strategic planning and policy decisions made in the coming years will ultimately define the long-term trajectory of the VPP market and the magnitude of its contribution to the global energy transition. In summary, the Virtual Power Plant is no longer a theoretical concept but a maturing "Smart Operating System" for the energy transition. Future research must continue to focus on the scalability of these models and their resilience against increasingly sophisticated cyber–physical threats.

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Abbreviations

AC-OPF	AC Optimal Power Flow
ADMM	Alternating Direction Method of Multipliers
ADN	Active Distribution Network
AI	Artificial Intelligence
ARIMA	Auto Regressive Integrated Moving Average
BESS	Battery Energy Storage System
BTM	Behind-the-Meter
C&CG	Column-and-Constraint Generation
CCER	China Certified Emission Reduction
CCS	Carbon Capture and Storage
CEA	Carbon Emission Allowance
CHP	Combined Heat and Power
CCHP	Combined Cooling, Heat, and Power
CPS	Cyber–Physical Systems
CUD	Control–Uncontrollability Decomposition
CVaR	Conditional Value-at-Risk
CVPP	Commercial Virtual Power Plant
DAM	Day-Ahead Market
DER	Distributed Energy Resource
DES	Distributed Energy Storage
DG	Distributed Generation
DGU	Dispatchable Generation Unit
DHN	District Heating Network
DLMP	Distribution Locational Marginal Pricing
DLR	Dynamic Line Rating
DMPC	Distributed Model Predictive Control
DoS	Denial of Service
DR	Demand Response
DRO	Distributionally Robust Optimization
DRL	Deep Reinforcement Learning
DSO	Distribution System Operator
ESS	Energy Storage System
EV	Electric Vehicle

FCAS	Frequency Control Ancillary Services
FDI	False Data Injection
FFR	Fast Frequency Response
FL	Federated Learning
GAN	Generative Adversarial Network
HVAC	Heating Ventilation Air Conditioning
IABC	Improved Artificial Bee Colony
ICNN	Input Convex Neural Networks
ICT	Information and Communication Technology
IGDT	Information Gap Decision Theory
IPT	Information Pipe Technology
ISO	Independent System Operator
KKT	Karush-Kuhn-Tucker
LAC-OPF	Linearized AC Optimal Power Flow
LLMs	Large Language Models
LMP	Locational Marginal Pricing
LOLP	Loss of Load Probability
LPF	Linear Power Flow
MCP	Market Clearing Price
MES	Multi-energy Systems
MEVPP	Multi-Energy Virtual Power Plant
MIP	Mixed-Integer Programming
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MPC	Model Predictive Control
MPEC	Mathematical Program with Equilibrium Constraints
NBS	Nash Bargaining Solution
P2G	Power-to-Gas
P2H	Power-to-Hydrogen (or Heat)
P2P	Peer-to-Peer
PCC	Point of Common Coupling
PDF	Probability Density Function
PEM	Point Estimation MethodV
PHFRL	Hierarchical Federated Reinforcement Learning
PV	Photovoltaic
RCC	Robust Capability Curve
REC	Renewable Energy Certificate
RES	Renewable Energy Source
RO	Robust Optimization
RTDS	Real-Time Digital Simulators
RTM	Real-Time Market
RTO	Regional Transmission Organization
SCADA	Supervisory Control And Data Acquisition
SoC	State of Charge
SOCP	Second-Order Cone Programming
TES	Thermal Energy Storage
TSO	Transmission System Operator
TVPP	Technical Virtual Power Plant
UT	Unscented Transform
V2G	Vehicle-to-Grid
VB	Virtual Battery
VES	Virtual Energy Storage
VG	Virtual Generator
VOLL	Value of Lost Load
VPP	Virtual Power Plant
VRE	Variable Renewable Energy
VSI	Voltage Security Index
VVC	Volt/VAR Control
WT	Wind Turbine

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