

Review

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Keywords: virtual power plants (VPPs); artificial intelligence (AI); machine learning; deep learning; reinforcement learning; distributed energy resources (DERs)



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Review

AI Driven Virtual Power Plants: a Comprehensive Review

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Abstract

The rapid proliferation of distributed energy resources (DERs), including photovoltaics, wind power, battery energy storage, and electric vehicles, has transformed traditional power systems into highly decentralized and data-rich environments. Virtual Power Plants (VPPs) have emerged as a key mechanism for aggregating these heterogeneous assets and enabling coordinated control, market participation, and grid-support functions. Recent advances in artificial intelligence (AI) have further elevated the scalability, autonomy, and responsiveness of VPP operations. This paper presents a comprehensive review of AI for VPPs, organized around a taxonomy of machine learning, deep learning, reinforcement learning, and hybrid approaches, and examines how these methods map to core VPP functions such as forecasting, scheduling, market bidding, aggregation, and ancillary services. In parallel, we analyze enabling architectural frameworks—including centralized cloud, distributed edge, hybrid cloud–edge collaboration, and emerging 5G/LEO satellite communication infrastructures—that support real-time data exchange and scalable deployment of intelligent control. By integrating methodological, functional, and architectural perspectives, this review highlights the evolution of VPPs from rule-based coordination to intelligent, autonomous energy ecosystems. Key research challenges are identified in data quality, model interpretability, multi-agent scalability, cyber-physical resilience, and the integration of AI with digital twins and edge-native computation. These findings outline promising directions for next-generation intelligent VPPs capable of delivering secure, flexible, and self-optimizing DER aggregation at scale.

Keywords: Virtual Power Plants (VPPs); Artificial Intelligence (AI); machine learning; deep learning; reinforcement learning; Distributed Energy Resources (DERs)

1. Introduction

With the rapid development of distributed energy resources (DERs), including solar photovoltaics, wind power, battery energy storage, and electric vehicles, the previously centralized and unidirectional power system is evolving into a more flexible and decentralized structure. These heterogeneous energy resources are often geographically dispersed and exhibit diverse operating characteristics and response times, which makes it increasingly difficult for traditional scheduling and management methods to maintain both efficiency and stability. To achieve higher levels of coordination and optimization, new control paradigms are emerging. Among them, VPPs have gained significant attention as a promising model that aggregates heterogeneous DERs into a unified, centrally managed entity capable of participating in electricity markets and supporting grid stability [1].

1.1. Evolution and Deployment of VPPs

The concept of VPPs originated in Europe in the early 2000s, aiming at enhancing the grid integration of distributed generation and improving overall system flexibility [2–4]. Early European research established the fundamental principles of distributed energy aggregation and system-level

coordination, which were subsequently validated through EU-funded pilot projects, most notably the FENIX program (2005–2009) [3,4]. Subsequent studies have indicated that the VPP concept, originating from these European initiatives, has progressively evolved into a commercially viable energy management framework that integrates small-scale generators, energy storage systems, and controllable loads via advanced information and communication technologies [5,6].

Nowadays, the total aggregated capacity operating under VPPs frameworks globally has surpassed approximately 35 GW [7], with major deployments in Germany, the United States, Australia, and China. In the United States, federal and state-level initiatives have accelerated the integration of distributed energy resources into grid operations. Programs such as the Department of Energy's Grid Modernization Initiative and the Inflation Reduction Act (IRA, 2022) have introduced strong policy and financial incentives for DERs aggregation and market participation [8].

Collectively, these efforts illustrate the growing maturity of VPPs as a foundational component of the global transition toward distributed, intelligent, and market-driven energy coordination.

1.2. Technological Foundations Enabling AI-Driven VPPs

In recent years, the rapid evolution of communication networks and computing infrastructure has provided key technical support for the large-scale application of AI in VPPs. With the maturity of 4G/5G cellular networks, various industrial IoT protocols, and cloud edge collaborative architectures, distributed energy devices can achieve more stable, low latency, and secure data exchange. At the same time, from edge computing modules such as NVIDIA Jetson and Orin to GPU cloud servers with powerful parallel computing capabilities, the improvement of computing hardware performance has significantly enhanced the feasibility of real-time data processing and AI reasoning.

Meanwhile, low Earth orbit (LEO) satellite Internet systems, exemplified by Starlink developed by SpaceX [9], have begun to play an important role in practical VPP deployments by providing a relatively independent communication medium for remote areas with limited connectivity. Hybrid communication architectures that combine terrestrial networks with satellite links enable VPP assets located in off-grid or communication-constrained regions to maintain essential data connectivity and control access.

Although these technological advancements have not altered the fundamental concept of VPPs, they have substantially expanded the scale and depth of AI-based coordination and control. Leveraging these infrastructures, intelligent computing can be deployed closer to the energy assets themselves, thereby shortening response paths, enabling localized optimization, and enhancing the scalability and resilience of the overall system.

1.3. The Role of Artificial Intelligence in VPPs

The operation of VPPs inherently involves uncertainty, heterogeneity, and dynamic interactions. Renewable energy generation is stochastic, demand patterns fluctuate, and real-time market conditions change rapidly.

To address these challenges, artificial intelligence (AI) has emerged as a critical enabling technology. Machine learning (ML) and deep learning (DL) techniques support high-precision forecasting of renewable generation, load demand, and market prices, while reinforcement learning (RL) and multi-agent optimization methods facilitate adaptive scheduling, dispatch, and bidding strategies. Through these AI-based approaches, VPPs are evolving from static, rule-based systems into autonomous, data-driven, and self-optimizing networks.

In recent years, industrial and research initiatives such as AutoGrid Flex [10], Siemens Grid Edge [11], and Schneider Electric's EcoStruxure distributed energy resource management (DERMS) platform [12] have demonstrated the feasibility and value of AI-integrated VPP operations, yielding enhanced forecasting accuracy, more efficient dispatch optimization, and more intelligent market participation.

1.4. Motivation and Structure of This Review

While the application of AI in VPPs has garnered significant attention, existing research remains fragmented, primarily focusing on specific applications such as prediction, optimization, or bidding, lacking a comprehensive understanding of how different AI paradigms collectively enhance VPPs performance.

Particularly noteworthy is the fact that most research emphasizes the contributions of individual algorithms, failing to establish a unified perspective on how AI technologies collectively improve prediction accuracy, operational efficiency, market adaptability, and system robustness. Representative examples include [13–19], and further related works.

This paper presents a comprehensive, algorithm-centric review of AI applications in VPPs. We systematically analyze the applications of ML, DL, and RL algorithms in key VPPs functional modules, including prediction, scheduling, aggregation, and market participation, and analyze how these technologies interact to form an intelligent control ecosystem.

Furthermore, we examine how advances in computing hardware (e.g., edge AI processors, GPU clusters) and increasingly mature communication infrastructures (e.g., 5G and satellite networks) provide the technological foundation for the large-scale deployment of these AI models. Although these developments are not the primary focus of this paper, they are recognized as key enablers for practical VPP implementations.

Finally, this paper also identifies key challenges and research opportunities, including the need for interpretable models, scalable multi-agent coordination, and hybrid AI frameworks that integrate prediction, optimization, and decision-making to build the next generation of smart VPPs.

To provide a clear structural overview of how this review is organized and how the different AI paradigms, functional modules, and comparative analyses are interconnected, Figure 1 presents the taxonomy and overall conceptual structure of the paper.

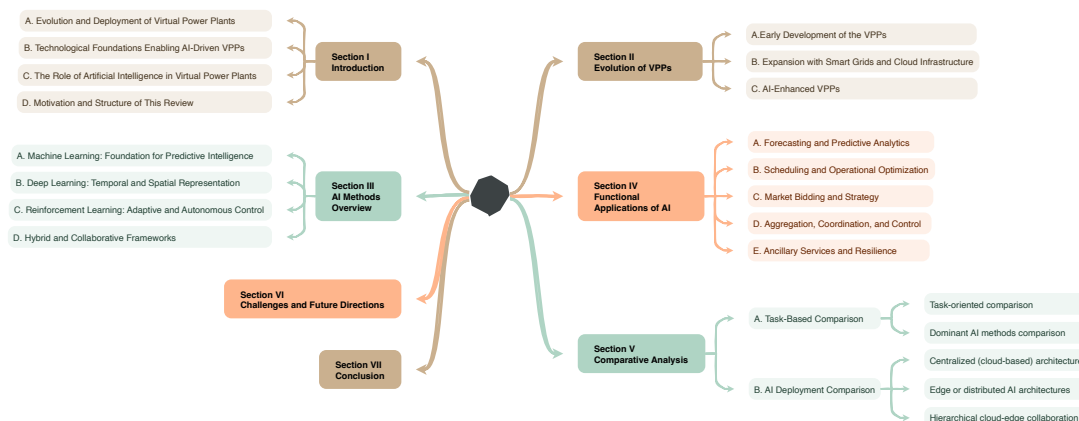


Figure 1. Taxonomy and structural overview

2. Evolution of VPPs: From Concept to Intelligence

The development of VPPs is the result of the ongoing interaction between communication technologies, computational intelligence, and energy system architecture. Each of the past few decades has brought a paradigm shift, from the early vision of coordinating distributed generation to the rise of autonomous, AI-driven energy networks today. This section traces the evolution and conceptual development of VPPs, highlighting the technological breakthroughs and representative research of each stage.

2.1. Early Development of the VPP Concept

The origins of VPPs can be traced to early 2000s Europe, particularly within Germany's Energiewende program, which sought to integrate growing renewable capacity into the national grid.

In 2002, Kirsten and Müller [2] were among the first to formally introduce the term “Virtual Power Plant”, describing a system that aggregates decentralized generators through information and communication technology based coordination. Early European demonstration projects, such as the E-Energy Initiative (2008), embodied this vision by linking small-scale combined heat and power (CHP) units, wind farms, and controllable loads via Supervisory Control and Data Acquisition (SCADA) systems and industrial Ethernet networks.

Building on this foundation, European research programs such as the EU-funded *FENIX* project (2005-2009) demonstrated practical aggregation of distributed generators and controllable loads across Spain and the United Kingdom [3,4]. In parallel, Pudjianto, Ramsay, and Strbac [1] provided one of the first formal academic definitions of VPPs, emphasizing its potential to enhance distributed generation integration and improve system flexibility.

At this stage, VPPs operated under centralized, rule-based control schemes, with fixed schedules and limited adaptability. Communication relied on wired networks and early 2G/3G mobile systems, restricting scalability and real-time responsiveness. Nonetheless, these early projects established the fundamental idea: that distributed energy resources could be orchestrated to behave as a single, flexible power entity.

2.2. Expansion with Smart Grids and Cloud Infrastructure

The following decade marked a pivotal transformation, with smart grids and cloud computing beginning to reshape the power systems. The widespread deployment of smart meters and IoT-level sensors enabled continuous and granular data collection from distribution networks and end users [20, 21]. During this period, cloud-based demand response and DERMS optimization architectures were proposed, most notably the cloud-based demand response framework introduced by Kim, Yang, and Thottan [22], together with household-level optimization methods such as the three-step demand-side management approach presented by Bakker et al. [23].

Utilities then began experimenting with cloud-hosted VPP or DERMS control centers capable of executing real-time demand response and distributed scheduling, leveraging the growing body of work on cloud computing for smart grids [21,24]. Meanwhile, the rise of machine-learning-based forecasting significantly improved short-term load prediction. Hong’s tutorial overview [25] demonstrated how regression and neural network models could be organized into a practical forecasting workflow applicable to power systems.

At the communications level, infrastructure evolved from 3G to 4G/LTE, providing lower latency and higher bandwidth for advanced metering and control applications [26,27]. In parallel, the adoption of open protocols such as MQTT [28] and Modbus TCP [29] reduced vendor lock-in and enabled interoperable, globally scalable communication frameworks for VPPs.

2.3. Emergence of AI-Enhanced VPPs

The period from 2016 to 2020 marked a crucial turning point in the development of AI, during which AI evolved from an auxiliary analytical tool into a core technology enabling the operation of VPPs. Early applications of deep learning demonstrated the potential of neural networks in renewable energy generation. Gensler et al. [30] applied long short-term memory (LSTM) networks to solar power generation forecasting, achieving significant improvements compared to traditional regression-based methods.

Meanwhile, RL also gained widespread attention as a dynamic scheduling and market participation strategy. Zhang et al. [31] constructed a real-time scheduling model for VPPs based on deep reinforcement learning, while Glavic and Fonteneau [32] provided a comprehensive review of reinforcement learning applications in power system operation and control. Together, these studies demonstrated that AI achieved a degree of autonomous and adaptive decision-making under market and grid uncertainties.

The rise of edge computing and GPU-accelerated embedded platforms, such as NVIDIA’s Jetson TX2 and Xavier, enabled inference tasks to be executed closer to data sources [33,34]. This technological

shift gave rise to a hierarchical control model: local edge nodes performed initial data processing and anomaly detection, while cloud controllers conducted global optimization.

Commercial deployments validated these advancements. AutoGrid Flex [10] in the United States and Next Kraftwerke [35] in Germany successfully integrated predictive analytics and automated bidding into real-world market operations. Taken together, these developments marked a shift from centralized coordination to intelligent decentralized coordination and signaled the emergence of AI-enhanced VPPs.

2.4. Convergence Toward Intelligent and Autonomous VPPs

Since 2020, the lines between energy management, AI, and telecommunications have become increasingly blurred. The advent of 5G wireless networks with latency below 10 milliseconds and massive device connectivity technically enabled the real-time coordination of thousands of distributed assets [36]. As highlighted by recent studies on 5G-enabled smart grids [37,38], 5G communication networks provided the reliability, ultra-low latency, and scalability required for next-generation distributed energy management and VPP applications.

At the same time, multi-agent reinforcement learning (MARL) began to redefine the control architecture of complex energy ecosystems. For instance, a residential-microgrid MARL framework demonstrated that autonomous agents negotiated local schedules and balanced system-wide objectives with user-level autonomy [15]. More broadly, Charbonnier et al. [39] presented a scalable coordination method in which centralised training enabled decentralised execution across distributed assets, indicating a viable pathway for next-generation VPPs to self-organise and adapt under dynamic grid and market conditions.

The integration of edge–cloud orchestration frameworks powered by containerized deployments (e.g. Kubernetes and its edge variants such as KubeEdge) and distributed time-series databases (e.g. TimescaleDB, Apache Cassandra) further enhanced scalability, resilience, and cyber-physical flexibility. Feng et al. [40] reviewed edge-computing architectures and use cases in smart grids, highlighting cloud–edge coordination patterns that enabled low-latency analytics and control. For the data layer, Pinheiro et al. [41] implemented a Cassandra-based SMACK stack (Spark, Mesos, Akka, Cassandra, Kafka) in a real microgrid, illustrating scalable storage for high-rate telemetry. Complementarily, Li et al. [42] described edge–cloud computing systems for smart grids and the evolution from centralized clouds to hybrid edge–fog–cloud architectures.

Li et al. [43] investigated resource orchestration in a hybrid cloud-edge architecture for smart grid fault detection systems, focusing on cross-layer computation and communication scheduling. Pan [44] examined a demand-response-oriented edge–cloud collaborative control framework, exploring how cloud, fog, and edge layers jointly performed energy-management tasks within the ubiquitous power Internet-of-Things (UPIoT) paradigm. The study outlined the system architecture, deployment models, and technical challenges of implementing hierarchical control in which edge nodes executed low-latency responses while cloud platforms handled large-scale optimization in smart grid applications.. Kempf et al. [45] refactored the open-source energy platform VOLTTRON into a cloud-native Kubernetes microservice architecture, demonstrating the scalability and flexible deployment capabilities of the EMS/VPP functionality in a containerized environment. Kim et al. [46] proposed a Kubernetes-based solution for modernizing the real-time front-end processor of a SCADA system, validating the applicability of container orchestration in power grid monitoring infrastructure. At the hardware level, edge processors dedicated to artificial intelligence, such as NVIDIA Jetson Orin and Google Coral Edge TPU, enhanced local decision-making and near–real-time inference capabilities [47,48].

Moreover, LEO satellite constellations and other non-terrestrial networks (NTNs) were increasingly leveraged to complement terrestrial 5G infrastructure, thereby extending VPP connectivity to remote and rural regions. Alam et al. [49] presented a satellite-based data collection architecture tailored for VPPs in rural areas, demonstrating the technical feasibility of integrating satellite links into VPP communications.

In summary, these advancements have transformed modern VPPs from centralized aggregators into self-learning ecosystems capable of continuous optimization and self-healing operation.

2.5. Timeline Overview and Convergence Analysis

Across two decades, three technological trajectories have converged to define the contemporary landscape of VPPs, As shown in Figure 2:

1. **VPPs development:** from early market-based aggregation concepts to AI-enabled forecasting, optimization, and autonomous VPPs;
2. **Communication & infrastructure evolution:** from SCADA/2G/3G systems to 5G, edge computing, and LEO satellite integration;
3. **AI technology evolution:** from statistical models to ML, DL, and RL frameworks supporting intelligent, adaptive VPP operation.

The intersection of these trajectories, particularly during the period from 2016 to 2020, marks a critical inflection point at which AI-driven VPPs became both technically feasible and economically viable, laying the foundation for the intelligent, decentralized energy ecosystems observed today.

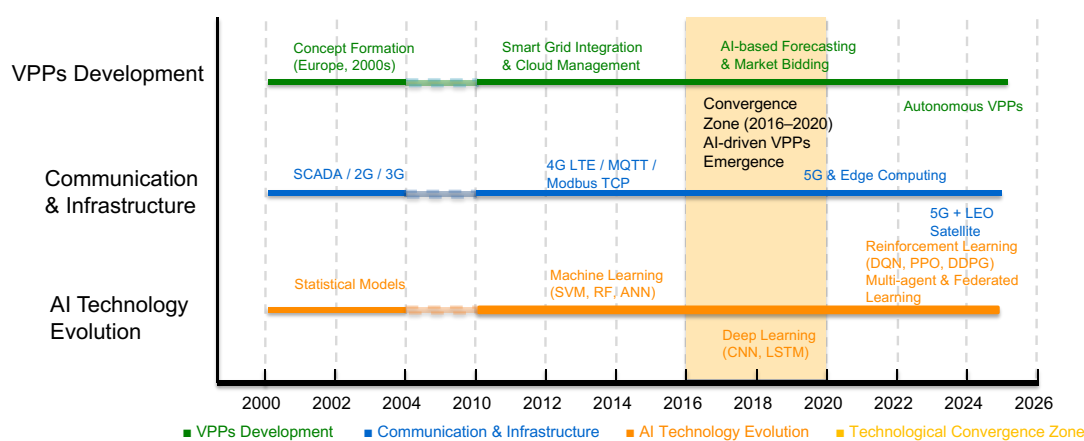


Figure 2. Technological convergence timeline of VPPs, communication, and AI development (2000–2025). The highlighted convergence zone (2016–2020) represents the emergence of AI-driven VPPs.

3. Overview of AI Paradigms for VPPs

AI is steadily transforming how VPPs are modeled, predicted, and operated. Early VPPs' implementations relied heavily on deterministic or rule-based optimization, which performed well under predictable conditions but proved inadequate in the face of increasing uncertainty and market volatility in renewable energy generation. As distributed energy systems become more dynamic, adaptive intelligence becomes crucial. AI provides a suite of computational tools that enable VPPs to learn from data, adapt to changing environments, and make coordinated decisions across multiple spatiotemporal scales.

The main branches of AI used in VPPs can be categorized into four types: ML for data-driven prediction, DL for extracting complex spatiotemporal patterns, RL for autonomous decision-making, and hybrid frameworks integrating multiple learning and control paradigms. These technologies collectively form the foundation of modern intelligent VPPs.

Figure 3 illustrates the overall framework of AI-driven VPPs, showing how field and market data flow through cloud and edge AI modules to enable forecasting, optimization, bidding, control, and diagnostic functions.

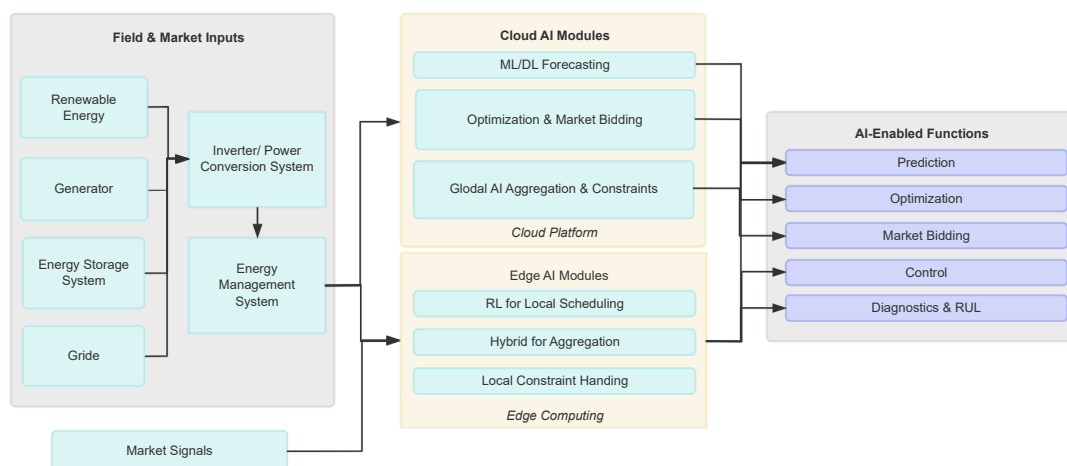


Figure 3. Overall framework of AI-driven VPPs with cloud and edge integration.

3.1. Machine Learning: Foundation for Predictive Intelligence

Machine learning forms the first layer of intelligence in VPPs. Its advantage lies in its ability to mine patterns from large datasets, transforming historical measurements of power generation, demand, and weather into actionable forecasts. Classic machine learning models, such as linear regression, support vector machines, random forests, and gradient boosting trees, are commonly used to predict short-term load or renewable energy generation, or to estimate electricity prices. These methods typically rely on carefully designed input features, such as temperature, solar irradiance, or time metrics, reflecting the domain knowledge of the system operator.

Due to their efficiency and transparency, machine learning models are highly attractive for operational forecasting and online control, especially where interpretability and accuracy are equally important. However, they often rely on manually designed features and can be insufficient in capturing the nonlinear, highly dynamic patterns in renewable energy-dominated grids [50,51]. This limitation naturally prompts researchers to adopt deep learning methods, which can automatically extract such patterns without explicit feature design.

3.2. Deep Learning: Temporal and Spatial Representation

DL has expanded the analytical capabilities of VPPs by enabling models to learn complex nonlinear relationships directly from data. Recurrent Neural Networks (RNNs), particularly architectures like LSTM and GRU, excel at capturing temporal dependencies, enabling efficient load, wind, and solar power forecasting across multiple time scales [52,53]. Convolutional Neural Networks (CNNs) and attention-based architectures, such as the Transformer, further extend this capability by learning spatial dependencies between distributed assets or weather fields.

In recent years, deep learning has also been applied to fault detection, anomaly identification, and energy storage diagnostics, helping operators predict problems before they impact system stability. With increasingly distributed computing resources, lightweight neural network models can even be deployed on edge devices to provide real-time intelligence and reduce reliance on centralized servers. Despite these advancements, deep networks also have their trade-offs: they require significant computational resources and are often considered "black boxes". This has spurred ongoing research into model compression, interpretability, and hybrid architectures that combine the expressive power of deep learning with classical control and optimization techniques.

3.3. Reinforcement Learning: Adaptive and Autonomous Control

While ML and DL focus on modeling and predicting patterns, RL goes a step further by learning how to act. In the context of VPPs, RL allows systems to discover optimal control strategies through trial and error and to adapt their behavior as operating conditions evolve. This paradigm is particularly effective for tasks such as energy storage scheduling, demand-side management, and market bidding,

where real-time decisions must balance multiple, often conflicting objectives, including cost, reliability, and equipment health.

A significant advantage of RL is its ability to operate under uncertainty without requiring precise environmental models. Recent research has explored multi-agent RL, where DERs or subsystems act as autonomous agents, collaborating towards a common goal. This distributed perspective aligns well with the decentralized nature of VPPs, enabling flexible resource coordination while maintaining scalability. However, RL still faces several challenges. Its training process can be unstable, heavily depends on how the reward function is designed, and often demands significant computational resources. To overcome these limitations, researchers are increasingly exploring hybrid reinforcement learning approaches that blend data-driven learning with rule-based control or supervised pre-training, aiming to strike a better balance between adaptability and reliability.

3.4. Hybrid and Collaborative Frameworks: Toward Integrated Intelligence

The future of artificial intelligence in VPPs lies in integration. Since no single paradigm can fully address the complexities of real-world power systems, researchers are beginning to fuse prediction, optimization, and control into hybrid intelligent frameworks. For example, the fusion of deep learning and model predictive control leverages neural networks to provide fast predictions for the Model Predictive Control (MPC) optimizer, enabling real-time use [54]. Another emerging direction is Federated Learning (FL), which allows multiple microgrids or sub-VPPs to share knowledge without exposing private data, a significant step towards achieving large-scale data privacy and collaboration.

Other promising tools include graph neural networks, which can capture spatial relationships between DERs and network nodes; and RL based on digital twins, which uses high-fidelity simulations to securely train and validate control policies before practical application. In summary, these approaches represent a shift from centralized control to distributed collaborative intelligence, where the cloud, edge, and device layers can continuously learn from each other. This hierarchical ecosystem enables faster adaptability, greater resilience, and more transparent coordination across the entire VPPs infrastructure.

3.5. Summary

Over the past two decades, AI methods for VPPs have evolved from basic statistical predictors to fully integrated and adaptive learning frameworks. ML lays the foundation for data-driven modeling; DL enhances the ability to represent complex spatiotemporal dependencies; RL enables autonomous and sequential decision-making; The emergence of hybrid frameworks unifies these paradigms to form a coherent, multi-level intelligent system. These methods together form the core computational toolbox that supports the design of modern intelligent VPPs. A concise comparison of the major AI paradigms, their input requirements, strengths, and limitations in VPPs applications is summarized in Table 1.

Table 1. Comparison of AI Paradigms for VPPs Applications

AI Paradigm	Representative Algorithms	Input Data	Strengths	Limitations
Machine Learning	SVR, Random Forest, Gradient Boosting	Historical generation, weather, load data	Simple structure, interpretable, fast training	Limited nonlinear modeling, weak adaptability
Deep Learning	CNN, LSTM, Transformer-GNN	Spatiotemporal and image-like data	Captures complex temporal-spatial features, high accuracy	Requires large datasets and GPU resources, black-box nature
Reinforcement Learning	DQN, MARL, Safe-RL	Real-time market and control data	Adaptive and autonomous decision-making	High training cost, unstable convergence
Hybrid AI Frameworks	MPC+DL, RL+Rule-based	Multi-modal (real + simulated) data	Combines interpretability and adaptability	Complex implementation, higher maintenance cost

These developments collectively redefine the concept of a VPPs, it is no longer merely a coordinated collection of distributed assets, but a self-optimizing, data-driven entity capable of intelligently responding to dynamic changes in the power grid and markets. The following sections will build upon this foundation to explore how these AI approaches are applied to specific functions of VPPs, such as prediction, scheduling and optimization, market bidding, aggregation, and ancillary service management.

4. Functional Roles of AI In VPPs

Building upon the algorithmic foundations discussed in Section III, we now turn to how AI actually powers the daily operations of VPPs. The core operations of intelligent VPPs revolve around five key modules: forecasting, scheduling and optimization, market bidding, aggregation and coordination, and ancillary services. Across these modules, AI has driven a transition from static, centralized control schemes to data-driven, adaptive, and cooperative decision-making systems.

4.1. Forecasting and Predictive Analytics

Forecasting is central to the operation of VPPs, impacting dispatch, market bidding, and reserve capacity planning. The integration of AI has significantly improved the accuracy and adaptability of forecasting models, enabling the utilization of heterogeneous datasets incorporating meteorological, market, and user behavior information. ML algorithms such as Support Vector Regression (SVR) and Random Forest (RF) remain effective for short-term forecasting of photovoltaic (PV) generation and total load demand [55,56]. However, their ability to model complex nonlinear relationships and time dependencies is limited, leading to a growing shift towards more expressive DL architectures.

Zhu et al. [57] proposed a BiLSTM-self-attention-Kolmogorov-Arnold Network (KAN) hybrid model for VPPs load forecasting, achieving a coefficient of determination $R^2 = 0.962$ and RMSE of 141.4 MW in a mid-sized aggregated system. Similarly, Sarathkumar et al. [13] applied an Adam-optimized LSTM (AOLSTM) model to predict generation and storage behavior within a day-ahead VPPs market framework. Compared with baseline models such as Random Forest and Gradient Boosting, the proposed model reduced the mean absolute error (MAE) by about 12.8% and achieved a lower root mean square error (RMSE), thereby enhancing overall prediction accuracy and bidding efficiency. Piotrowski et al. [55] proposed a hybrid ensemble forecasting framework for two-day-ahead wind power generation. The study showed that the combined ML-DL model achieved higher accuracy than individual approaches, with the RMSE and MAE values reduced by approximately 8% compared to the best single-model baseline. Li et al. [58] proposed an AI-based method for VPPs load forecasting and scheduling, combining forecasting with scheduling optimization to improve operational efficiency. Zhou et al. [14] introduced a Transformer-based spatiotemporal graph neural network for short-term

multi-energy load forecasting. Their model achieved 10–15% lower MAE and RMSE compared to conventional deep learning baselines, and significantly improved the correlation between electricity, heating, and cooling load predictions. In addition, Krstevska et al. [59] developed an analytical intelligent forecasting framework that combines artificial intelligence models with optimization strategies to improve the performance and interpretability of VPPs.

Beyond methodological advancements, numerous studies [24,40,44] highlighted the importance of multi-source data fusion in improving forecast robustness. For example, meteorological sensor data, satellite imagery, and IoT-based asset data were jointly used to construct spatiotemporal learning frameworks, thereby providing more stable forecasts for geographically distributed resources.

At the industrial scale, Next Kraftwerke [60] applied AI-enhanced solar and wind energy forecasting technology to coordinate over 10 gigawatts of DERs in real time, demonstrating the practical value of intelligent forecasting in large-scale portfolio management.

Despite these advancements, the forecasting accuracy of VPPs remained limited by data quality, latency, and the propagation of forecast uncertainty to downstream decision-making modules. Prior work showed that missing data, noisy sensor measurements, asynchronous sampling intervals, and network-induced delays degraded both forecasting performance and subsequent optimization or scheduling processes [14,21,42]. These limitations underscored the need for more resilient data pipelines, uncertainty-aware learning models, and robust edge–cloud coordination mechanisms.

4.2. Scheduling and Operational Optimization

Scheduling and real-time operation optimization are central to the efficient operation of VPPs. VPPs must dynamically coordinate DERs to meet load demand, participate in the electricity market, and ensure system reliability that all under cost and uncertainty constraints. Traditional control strategies, such as Mixed Integer Linear Programming (MILP) and Model Predictive Control, face challenges in the typical high-dimensional stochastic environment of modern VPPs. This has led to an increasing adoption of AI, particularly RL, for adaptive, scalable, and data-driven decision-making.

Recent research demonstrated the growing maturity of RL-based scheduling frameworks. Fang et al. [15] proposed a MARL framework for residential microgrids, in which distributed agents coordinated through a balance selection mechanism. Their method outperformed single-agent baselines in both fairness and cost minimization. Guo and Gong [61] further improved this approach by integrating priority experience replay into a hybrid advanced RL architecture for multi-microgrid management, achieving faster convergence and better inter-grid node cooperation. Zhang et al. [16] designed a deep reinforcement learning-based scheduling strategy for energy hub clusters, achieving significant cost reductions and greater resilience under operational uncertainty. Extending this trajectory, Li et al. [62] introduced a Physically Informed Deep Reinforcement Learning (PI-DRL) architecture that directly integrated system physical characteristics into the reward structure, thereby improving the interpretability and robustness of agent scheduling decisions under diverse distributed energy resource conditions.

Beyond pure reinforcement learning methods, hybrid AI optimization approaches emerged as a promising paradigm. These frameworks combined the adaptability of learning-based policies with the structure and reliability of traditional control strategies. For example, Conte et al. [63] proposed a hybrid AI management system for renewable energy communities that combined reinforcement learning with a constraint-based solver to achieve optimal scheduling while incorporating social and economic considerations. Alabi et al. [64] developed a hybrid non-exact optimal scheduling framework tailored for VPPs, integrating heuristic algorithms and optimization procedures to address uncertainties in demand response and renewable generation. Similarly, Panahzari et al. [65] designed a hybrid deep learning optimization algorithm with network resilience for distributed energy resource control, effectively addressing both physical disruptions and cyber threats.

These advances collectively represent a shift towards truly adaptive VPPs systems: architectures capable of learning and adapting in real time, leveraging both historical and real-time data, and coordinating complex assets without requiring explicit full-system modeling.

4.3. Market Bidding and Trading Strategies

Participating in the electricity market requires VPPs to develop optimal bidding and trading strategies to balance profit maximization, risk management, and system reliability in a volatile market environment. AI technology has become a powerful driving force in this field, enabling VPPs to predict market prices, assess operational risks, and autonomously adjust their bidding behavior.

Early research primarily relied on ML regression models to predict market clearing prices, forming the basis of rule-based bidding frameworks. For example, Sun et al. [17] developed a price prediction–assisted bidding strategy for day-ahead markets, in which a gradient boosting regression model predicted hourly prices and guided subsequent optimization, significantly reducing imbalance penalties compared to static bidding schemes. However, such data-driven but static models often failed to capture the dynamic feedback between market decisions and participant interactions.

To address this limitation, RL was widely adopted for adaptive bidding and trading. Stanojev et al. [18] applied a safety reinforcement learning framework to strategic bidding for VPPs in the day-ahead market, enabling participants to learn bidding strategies that maximized returns while explicitly limiting risk exposure and avoiding violations. Similarly, Mao et al. [66] proposed a joint market rolling bidding strategy that utilized deep reinforcement learning to coordinate trading decisions across multiple time spans, thereby improving return stability and responsiveness to market volatility.

Beyond individual learning agents, game theory and cooperative AI models were also used to capture the competitive behavior of multiple VPPs or market entities. Liu et al. [67] used cooperative game theory to construct a coalition-based bidding model for VPPs participating in the joint electricity–carbon market, demonstrating that the model improved profits and achieved a fair cost–benefit allocation among distributed energy participants. Complementary approaches, such as the robust bidding model proposed by Nemati et al. [68], utilized AI-assisted optimization through probabilistic and distributed robustness formulations to hedge against uncertainties in renewable energy and markets.

Despite these advances, several challenges remain, especially those related to data privacy, the interpretability of AI-based bidding strategies, and adherence to regulatory requirements. Future research is expected to focus on explainable learning architectures, privacy-preserving joint bidding, and multi-agent market simulation environments, all of which will enhance strategic transparency while ensuring fair and secure market participation.

4.4. Aggregation, Coordination, and Control

Aggregation is central to the functionality of a VPPs, enabling the integration of heterogeneous DERs, including photovoltaic systems, battery banks, and flexible loads, into a single, dispatchable virtual entity. Achieving this requires not only real-time visibility and control but also intelligent coordination across different devices, subsystems, and network layers.

Recent advances in MARL facilitated the development of decentralized coordination, in which each agent (e.g., an inverter, energy storage node, or microgrid) learned its own control strategy while collectively optimizing system objectives. For example, Li and Mohammadi [69] proposed a MARL-based distributed coordination scheme that incorporated a centralized critic with decentralized actor networks, demonstrating robust convergence across 50 DER agents under stochastic market signals.

To further leverage the physical topology of energy networks, graph-based artificial intelligence models, particularly graph neural networks (GNNs), were introduced. Zhang et al. [70] constructed a GNN architecture that achieved state estimation at the VPP level by modeling energy and voltage relationships between nodes. In a test case with 118 nodes, their method reduced estimation error by 15% compared to the traditional Kalman filter. Complementing this, Yu et al. [71] proposed a power system state estimation framework based on distributed Graph Convolutional Network (GCN), demonstrating that GNNs learned complex spatial correlations between nodes even under sparse or noisy measurement conditions, which was crucial for distributed VPP architectures.

Additionally, privacy and communication constraints sparked interest in FL frameworks for VPPs. Taheri [19] proposed a multi-task fuzzy logic method in which distributed energy clusters independently trained local models for power prediction and control while sharing only encrypted gradients. In an experimental environment with 20 devices, the fuzzy logic method outperformed centralized training in protecting data privacy without sacrificing control accuracy.

Overall, these technologies mark a shift from traditional SCADA-based architectures to edge-cloud collaborative ecosystems. In such ecosystems, intelligence is increasingly embedded at the edge for real-time response, while central nodes are responsible for long-term planning and optimization. This type of architecture is crucial for extending VPPs control to thousands of devices across geographical, market, and ownership boundaries.

4.5. Ancillary Services, Fault Detection, and System Resilience

Ancillary services (such as frequency regulation, reactive power control, and fault detection) are crucial for maintaining the stability and reliability of power systems, especially with the increasing integration of intermittent DERs into VPPs. AI technologies, particularly RL and DL, have shown great potential in enabling VPPs to autonomously provide these services in real time.

Lou et al. [72] proposed a deep reinforcement learning (DRL)-based control framework for reactive power and voltage support in VPPs. Their strategy dynamically adjusted the reactive power output of DERs, thereby stabilizing the local voltage curve and outperforming traditional voltage/reactive power (Volt/VAR) methods in both convergence speed and regulation accuracy. Similarly, Li et al. [73] developed a multi-agent DRL model for community VPPs to provide primary and secondary frequency regulation services, exhibiting improved adaptability and coordination under varying load and generation conditions.

Beyond AI control, robust optimization techniques were also explored. Vafa et al. [74] constructed a robust dispatch model for renewable-energy VPPs participating simultaneously in both energy and ancillary services markets. This model considered uncertainties in renewable generation and achieved reliable dispatch of both active and reactive power. Complementing this, Liu et al. [75] proposed a reinforcement learning-based decision-making architecture for urban VPPs, enhancing their ability to provide ancillary services while addressing environmental uncertainties.

Fault detection and system resilience were also critical components. Prakash et al. [76] surveyed battery storage systems used for ancillary services and emphasized the importance of early fault identification and health-aware dispatch. While traditional rule-based systems often lacked adaptability, AI-enhanced digital twins and predictive maintenance frameworks were used to detect anomalous operating conditions. These methods included autoencoder-based anomaly detection in DERs and voltage pattern recognition based on LSTM models [76].

In summary, these studies highlighted the shift of VPPs toward greater intelligence, autonomy, and resilience, enabling them to provide ancillary services in complex and dynamic environments. Several challenges remained, including the integration of AI strategies with physical system constraints, the assurance of cyber-physical security, and compliance with evolving grid regulations.

4.6. Discussion

The increasing prevalence of AI in the core functions of VPPs reflects a broader transformation in how distributed energy systems are managed and optimized. Modern VPPs are no longer confined to static or rule-based scheduling, but are evolving into intelligent, adaptive entities capable of handling the complexities of real-world grid environments.

This shift benefits from AI models' ability to capture nonlinear relationships, learn from heterogeneous and time-varying data sources, and generate control strategies that address supply and demand uncertainties. Whether predicting renewable energy output, coordinating large DERs clusters, or participating in dynamic electricity markets, AI enables more proactive and responsive operating models.

Importantly, the integration of various artificial intelligence technologies from DL and RL to graph and federated frameworks marks the development of AI towards integrated system level intelligence. These developments foreshadow the emergence of VPPs in the future, which cannot only aggregate resources but also autonomously reason, learn, and act, thereby combining operational efficiency with resilience and market responsiveness.

Table 2 summarizes these findings and illustrates the dominant AI methods used for each core VPPs function, along with representative works and key achievements.

Table 2. AI Methods and Representative Achievements for VPPs Functions

Functional Roles	Dominant AI Methods	Representative Works	Key Achievements
Forecasting and Predictive Analytics	LSTM, BiLSTM-KAN, Transformer-GNN, SVR + RF	[13,14,55,57–60]	Accurate multi-energy forecasting; improved bidding via joint prediction–dispatch models
Scheduling and Operational Optimization	RL, MARL, PI-DRL, Hybrid AI + MPC	[15,16,61–65]	Adaptive real-time scheduling; cyber-resilient hybrid frameworks
Market Bidding and Strategy	Safe RL, Game Theory, Distributionally Robust Optimization	[17,18,66–68]	Dynamic bidding with risk constraints; strategic profit maximization in joint markets
Aggregation, Coordination, and Control	MARL, GNN, Federated Learning	[19,69–71]	Decentralized coordination; privacy-preserving edge intelligence; improved state estimation
Ancillary Services and Resilience	DRL, Autoencoders, Digital Twins	[72–76]	Autonomous frequency/voltage control; predictive fault detection and maintenance

5. Comparative Analysis and Discussion

This section provides a comprehensive comparison of the major AI methods, examining their evaluation metrics, operational characteristics, and implementation trade-offs. By combining quantitative benchmarks with insights from published case studies, the analysis aims to present a clear and unified view of how different AI frameworks perform under real-world VPPs operating conditions.

5.1. Evaluation Dimensions

To enable a consistent and meaningful comparison across different AI-based strategies in VPPs, six core evaluation dimensions are commonly used. These dimensions capture not only technical performance but also practical considerations in deployment and operation.

Predictive Accuracy: Accurate forecasting of renewable generation, load demand, and market prices is essential for reliable VPPs operation. Performance is typically evaluated using statistical metrics such as MAE or RMSE. Forecasting errors propagate through subsequent control layers, making model choice and temporal resolution critical.

Operational Performance: This dimension reflects how well a control policy meets real-world objectives. Metrics include total cost reduction, renewable integration rates, and compliance with operational constraints. In learning-based systems, additional indicators like reward convergence or constraint violation frequency may also be used.

Robustness and Uncertainty Handling: Real-world systems are exposed to noisy inputs, unpredictable events, and missing data. Robust control architectures should maintain performance under such conditions, often by incorporating probabilistic models or hybrid learning structures that can adapt in real time.

Scalability and Distributed Capability: As the number of connected DERs grows, scalable architectures become critical. Decentralized coordination strategies such as multi-agent systems or

federated learning can alleviate centralized bottlenecks while preserving local autonomy, albeit at the cost of added communication complexity.

Computational and Deployment Cost: Practical deployment requires AI models to be efficient. This includes manageable training cost, low inference latency, and compatibility with edge devices. Lightweight architectures or model compression techniques are often employed to meet these constraints.

Interpretability and Operability: In market-regulated or safety-critical applications, transparency is essential. Models, which offer insight into their decisions through interpretable layers, rule constraints, or human-readable outputs, enhance operator trust and facilitate manual intervention when needed.

5.2. Task-Based Comparison

The cross functional analysis of prediction, scheduling, bidding, aggregation, and ancillary services reveals different patterns in the selection and effectiveness of artificial intelligence methods. It is best to solve *Forecasting* tasks through a hybrid deep learning model that integrates spatiotemporal data sources. Its spatiotemporal generalization ability, combined with the architecture of Transformer and graph neural network, demonstrates desirable performance in multi energy prediction scenarios. *Scheduling and dispatch* tasks increasingly rely on RL, especially hybrid reinforcement learning model predictive control methods. These combinations provide higher adaptability and network resilience for dynamic environments. *Market bidding* adopts cooperative and risk aware learning strategies. Methods such as secure reinforcement learning and game theory learning frameworks are particularly suitable for real-time bidding under fluctuating conditions, including coupled electricity markets. Scalable artificial intelligence architecture facilitates *Aggregation and coordination*. Multi agent reinforcement learning, federated learning, and graph neural networks can achieve decentralized control and coordination of large-scale DERs clusters, while ensuring data privacy and reducing communication overhead. Deep reinforcement learning, digital twin frameworks, and fault diagnosis algorithms enhance *Ancillary services and system resilience*. These technologies support predictive maintenance, autonomous frequency and voltage regulation, and real-time disturbance response, thereby improving the reliability of the power grid.

In summary, the comparative results indicate that no AI method can be universally applicable to all VPPs functions. On the contrary, the best choice is achieved by adjusting AI technology for specific tasks, and these adjustments should follow the evaluation dimensions outlined in Section 5.1. Table 3 provides a comprehensive evaluation for each tasks. This highlights the importance of modular and context aware AI system design in developing intelligent and flexible VPPs. While Table 3 provides a task-oriented comparison, it is also essential to evaluate the AI paradigms themselves. Table 4 summarizes the horizontal comparison of dominant AI methods used in VPPs research across the same six evaluation dimensions. This cross-method analysis highlights the trade-offs between interpretability, computational efficiency, and scalability among machine learning, deep learning, reinforcement learning, and hybrid frameworks.

Table 3. Comprehensive Evaluation of AI Method Trends Across VPPs Functional Tasks and Evaluation Dimensions

Task	Accuracy	Operational Performance	Robustness	Scalability	Computational Cost	Interpretability
Forecasting [13, 14,55,57–60]	High ($R^2 > 0.95$ with Transformer and BiLSTM-KAN hybrids)	Strong temporal-spatial generalization; effective for day-ahead planning	Moderate; sensitive to data noise and outliers, improved via probabilistic ensembles	Moderate (site-level aggregation)	Moderate to High	Moderate (attention-based interpretability)
Scheduling [15, 16,61–65]	Moderate (learning stability depends on reward design)	High; achieves cost reduction and constraint compliance in real time	High with hybrid MPC-RL; resilient to uncertainties and partial observations	Low (centralized RL) → High (MARL)	High (training and simulation cost)	Low, improved with rule fusion or physics-informed RL
Bidding [17,18, 66–68]	High for price forecasting; Moderate for adaptive bidding agents	High profitability and risk balance via Safe RL / Game Theory	Moderate to High with robust optimization and ensemble forecasting	Moderate (market scale dependent)	Moderate	Low to Moderate (depends on policy explainability)
Aggregation [19, 69–71]	High (topological estimation accuracy using GNN)	High system-level efficiency and cooperative energy balance	High via fault-tolerant MARL and privacy-aware FL	High (decentralized multi-agent scalability)	Moderate to High (edge-cloud computation)	Moderate (GNN attention visualization aids interpretation)
Ancillary Services [72–76]	Moderate (measurement-driven DRL / Autoencoder models)	High; maintains frequency and voltage stability under dynamic loads	High (anomaly detection and redundant control structures)	Moderate (edge deployment scenarios)	High (real-time control loop)	Low to Moderate (deep models require post-hoc explainers)

Table 4. Cross-Method Comparative Analysis of AI Techniques for VPPs

AI Method	Accuracy	Operational Performance	Robustness	Scalability	Computational Cost	Interpretability
Machine Learning	Moderate to High (feature-driven)	Moderate (effective for short-term forecasting)	Moderate (sensitive to feature bias and data noise)	High (lightweight and easily parallelized)	Low	High (transparent and explainable)
Deep Learning	High (spatiotemporal accuracy, low MAE/RMSE)	High (robust pattern extraction and multi-energy prediction)	Moderate (requires large data and regularization)	Moderate (depends on data and hardware)	High (training intensive)	Low (black-box; improved via attention or SHAP)
Reinforcement Learning	Moderate (policy convergence dependent on reward design)	High (adaptive decision-making in dynamic environments)	Moderate (training instability under uncertainty)	Low to Moderate	High (simulation and training cost)	Low (policy not interpretable)
Multi-Agent RL	Moderate	Very High (supports distributed coordination and negotiation)	High (fault-tolerant and self-adaptive)	High (decentralized learning)	Very High (multi-agent computation)	Low
Graph Neural Network	High (captures topological correlations)	High (effective in state estimation and coordination)	High (robust to incomplete data)	High (parallel node-level scalability)	Moderate	Moderate (attention-based interpretability)
Federated / Hybrid AI	High (aggregated learning across devices)	High (balancing accuracy, privacy, and adaptability)	High (resilient to communication failures)	Very High (distributed and privacy-preserving)	Moderate	Moderate (global model explainable via shared gradients)

5.3. Centralized vs. Distributed AI Deployment

The architectural design of an AI deployment plays a decisive role in the performance, scalability, and resilience of a VPPs. Based on the location of computation and learning, three main paradigms can be distinguished in research prototypes and industrial implementations: centralized architecture, distributed architecture, and layered architecture.

In *centralized (cloud-based) architectures*, all computational tasks, including model training and inference, are performed in a data center or cloud environment. Such architectures have access to complete historical and real-time datasets, enabling large-scale deep learning models with superior predictive accuracy and global optimization capabilities. However, they suffer from inherent limitations such as communication latency and dependence on network bandwidth, which restricts their application in environments with sub-second control loops and where communication reliability cannot be guaranteed.

In contrast, *edge or distributed AI architectures* delegate model inference (and in some cases, local retraining) to controllers located near DERs. By reducing communication dependencies, these architectures enable low-latency operation and increased resilience under intermittent connectivity conditions, especially when combined with 5G or LEO satellite networks. However, the limited compute and storage capacity of edge devices restricts model complexity and requires frequent parameter synchronization to maintain global model consistency.

To reconcile the complementary advantages of these two paradigms, *hierarchical cloud-edge collaboration* has emerged as a promising hybrid approach. In this architecture, the cloud layer performs global model training, prediction, and day-ahead optimization, while the edge layer performs real-time inference, local corrections, and autonomous decision-making. Such designs have been applied to commercial energy management platforms such as AutoGrid Flex and Siemens Grid Edge, achieving end-to-end scheduling latency of less than 100 milliseconds and striking a good balance between accuracy, responsiveness, and reliability.

To provide a clearer comparative view of these architectural paradigms, including centralized, distributed, hybrid, and emerging cloud-native frameworks. Table 5 summarizes their data flow structures, communication technologies, and respective advantages and limitations.

Overall, the evolution from centralized to hierarchical architectures is a key step in building a scalable, resilient, and intelligent VPPs ecosystem capable of operating efficiently on heterogeneous communication and compute infrastructures.

In practice, we are increasingly seeing the emergence of hybrid strategies. Cloud based predictive models utilize large datasets and powerful processors for long-term planning. Control and scheduling logic for edge processing, using models optimized for speed and robustness. This hierarchical approach acknowledges that different parts of the VPP ecosystem have different needs, and the most effective solution comes from matching appropriate tools with appropriate tasks.

Table 5. Comparison of VPPs Architectural Frameworks: Centralized, Distributed, Hybrid, and Cloud-Native

Architecture Type	Data Flow and Computation Location	Communication Technology	Advantages	Limitations
Centralized (Cloud-based)	All computation and storage handled in cloud or data center; global dataset aggregation [15,21,22,24]	LTE/4G/5G backbone	High global optimization accuracy; full data visibility	High latency; network dependency; limited local autonomy
Distributed (Edge-based)	Computation executed near DERs nodes or microgrids [15,19,69]	5G, Wi-Fi, or wired Ethernet	Low latency; strong resilience under intermittent connectivity; privacy-preserving learning	Limited local compute resources; frequent model synchronization required
Hybrid Cloud-Edge	Cloud performs global training and optimization; edge handles local inference and control [40,42-44]	5G + Satellite (Starlink) links [9,49]	Balances accuracy and response speed; scalable hierarchical control	Requires complex orchestration; potential data synchronization cost
Cloud-Native / Containerized	EMS/VPPs microservices deployed via Kubernetes and containers [45,46]	5G / LAN / cloud API	Highly scalable; modular and easily maintainable; supports continuous deployment	Demands advanced IT infrastructure and orchestration expertise

6. Challenges and Future Directions

Although the application of AI in VPPs is becoming increasingly common, achieving large-scale, reliable, and intelligent deployment still faces significant challenges.

One of the major issues is the fragmentation, inconsistency, and difficulty in accessing data. VPPs rely on data streams from various sources such as solar inverters, batteries, building loads, market prices, and more. However, due to different data sources, their formats and temporal dimensions are often inconsistent. Data standardization greatly increases the difficulty of integration, while privacy restrictions also hinder data sharing among stakeholders. Even with the most advanced models, reliability will be greatly compromised without clean, representative, and sufficient data support.

In addition to data limitations, algorithms also face many challenges. DL and RL provide powerful modeling tools, but their black-box nature has raised concerns about accuracy. Operators and regulatory agencies are unwilling to hand over control of critical tasks to a “black box” system. Despite the rapid development of AI technology, its application in the field of power systems is still immature. More fundamentally, models trained within a single geographic region or regulatory framework are often unable to generalize to other regions. Solving this problem requires not only algorithmic innovations such as transfer learning and secure reinforcement learning, but also more powerful pre-deployment testing and simulation environments, such as digital twin technology. Therefore, the importance of digital twin technology is becoming increasingly prominent.

Another key challenge is balancing model performance and computational complexity. In the operations of large VPPs, high-performance architectures such as Transformer-based predictive networks, MARL, and digital-twin-assisted control can provide excellent accuracy and adaptability, but their resource requirements often exceed real-time operational capabilities. Long training cycles, high inference latency, and expensive hardware remain obstacles to actual deployment. In contrast, lightweight models that combine deep learning with model predictive control (MPC) or heuristic rules are more suitable for industrial applications. These systems sacrifice some modeling complexity in exchange for faster response times and better interpretability—features that are crucial in daily control and

market scheduling. In environments where data is scarce or resources are limited, traditional machine learning and rule-based methods are still feasible because reliability and transparency are often more important than small precision improvements. In practice, many modern VPPs adopt a layered or hybrid architecture: cloud-based predictive models are responsible for long-term planning, while edge controllers are optimized for speed and robustness. This hierarchical approach fully considers the diversity of computing and operational requirements in the VPP ecosystem and emphasizes that effectiveness depends on matching appropriate tools to appropriate tasks.

Scalability further compounds these challenges. As the number of distributed units in VPPs increases from tens to thousands, each device has its unique response time, constraints, and communication latency. How to coordinate these assets in real time without consuming too much bandwidth or compromising security, as well as how to implement a reasonable cloud–edge architecture and intelligent allocation, are challenges we must face. Cloud servers excel at long-term prediction and optimization, but edge nodes must quickly process local decisions with limited computing power. The hybrid approach of training in the cloud and deploying compressed models to the edge is becoming increasingly common, while edge-native learning methods represent a promising frontier.

These challenges also bring new opportunities. Reasonable utilization of models can help fill data gaps and create richer training scenarios. Graph-based methods have shown great potential in capturing the relational structure of power networks. Federated learning and privacy-protection frameworks can unleash collaborative intelligence between utility companies without centralizing sensitive data. At the same time, advances in 5G and satellite communication technology will expand the geographic coverage of VPPs, especially in rural or underserved areas.

With the continuous development of artificial intelligence, building truly intelligent and resilient VPPs requires not only better algorithms but also a holistic effort that combines infrastructure, interpretable models, deployment, and continuous learning.

7. Conclusions

Over the past two decades, VPPs have shifted from centralized, rule-based coordination to a distributed, intelligent, and data-driven model. The progress of artificial intelligence, communication infrastructure, and computing hardware has provided strong support for this transformation.

This review comprehensively analyzes many studies that link AI methods with the functional and operational requirements of VPPs. The third section of this paper briefly describes the classification of AI, ML, DL, RL, and hybrid or emerging frameworks, and focuses on how each method meets the specific challenges of prediction, control, and optimization. Section IV reviews the articles that map these AI methods to VPPs, from forecasting, scheduling, market bidding, aggregation, to ancillary services. The results show that deep learning is superior in prediction accuracy, while reinforcement learning and hybrid reinforcement learning dominate in adaptive control and decision-making, and hybrid frameworks achieve the best balance between performance, interpretability, and scalability. Section VI identifies the remaining challenges and presents the authors' view of the future development directions of VPPs according to these challenges.

In summary, the future architecture of VPPs will evolve toward a multi-layer, task-aware artificial intelligence ecosystem, where prediction, optimization, and control modules interact through collaborative intelligence distributed across both edge devices and cloud platforms. The integration of AI with 5G/satellite communication, edge computing, and secure data infrastructures will accelerate the deployment of large-scale, autonomous VPPs, even in remote regions. As a result, next-generation digital power systems will increasingly depend on the seamless fusion of advanced AI algorithms with the underlying energy network infrastructure.

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