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Deep Reinforcement Learning-Based Multi-Objective Optimization for Virtual Power Plants and Smart Grids: Maximizing Renewable Energy Integration and Grid Efficiency

Xinfa Tang * and Jingjing Wang

School of Economic Management and Law, Jiangxi Science and Technology Normal University, Nanchang 330013, China; jingjingw2024@126.com
* Correspondence: xinfatang@sina.com

Abstract: The rapid development of renewable energy necessitates advanced solutions that address the volatility and complexity of modern power systems. This study proposes an AI-driven integrated optimization framework for a Virtual Power Plant (VPP) and Smart Grid, aiming to enhance renewable energy utilization, reduce grid losses, and improve economic dispatch efficiency. Leveraging deep reinforcement learning (DRL), this framework dynamically adapts to real-time grid conditions, optimizing multi-objective functions such as power loss minimization and renewable energy maximization. This research incorporates data-driven decision-making, blockchain for secure transactions, and transformer architectures for predictive analytics, ensuring its scalability and adaptability. Experimental validation using real-world data from the Shenzhen VPP demonstrates a 15% reduction in grid losses and a 22% increase in renewable energy utilization compared to traditional methods. This study addresses critical limitations in existing research, such as data rigidity and privacy risks, by introducing federated learning and anonymization techniques. By bridging theoretical innovation with practical application, this work contributes to the United Nations' Sustainable Development Goals (SDGs) 7 and 13, offering a robust pathway toward a sustainable and intelligent energy future. The findings highlight the transformative potential of AI in power systems, providing actionable insights for policymakers and industry stakeholders.

Keywords: Virtual Power Plant; Smart Grid; AI-driven optimization; renewable energy; deep reinforcement learning

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1. Introduction

In the context of the global energy transition, Virtual Power Plants (VPPs), as an important innovative model of distributed energy management, have attracted wide attention. By integrating distributed energy sources, such as wind and solar, with storage systems, VPPs can significantly increase the utilization of renewable energy and enhance the flexibility and reliability of the power system. By utilizing advanced information technology and communication technology, the Smart Grid can realize real-time monitoring and management of the power system and quickly respond to load changes and failures [1]. The combination of a VPP and Smart Grid not only promotes the integration and management of renewable energy, but also improves the efficiency of energy utilization and provides strong support for the modernization of the power system. Figure 1 shows a VPP data interaction architecture flowchart. This figure illustrates how VPPs interact with and integrate into the Smart Grid framework.

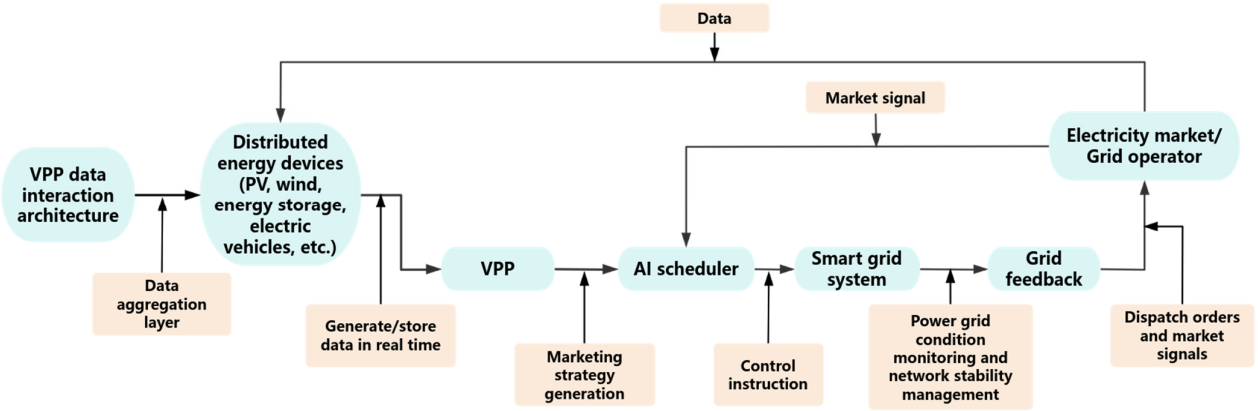


Figure 1. VPP data interaction architecture flowchart.

This work contributes to the United Nations' Sustainable Development Goals (SDGs), specifically SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). By enhancing the integration and utilization of renewable energy through AI-driven optimization algorithms, it directly contributes to ensuring access to affordable, reliable, and modern energy services for all. By reducing carbon emissions and promoting the use of clean energy sources, this study supports global efforts to combat climate change and its impacts. In addition to environmental and economic sustainability, this study also explores the social dimension of sustainability. The integration of a VPP and Smart Grid can significantly improve energy equity and user participation. By supporting distributed energy and promoting user participation in energy management, this integration enables communities and individuals to play a more active role in the energy transition. It not only improves the overall efficiency and reliability of the power system, but also ensures that the benefits of renewable energy are distributed more equitably throughout society. By using real-time monitoring and management, the Smart Grid provides users with more flexible options for using electricity, thereby increasing user satisfaction and promoting social well-being.

1.1. Characteristics of VPPs

A VPP is a system that integrates multiple distributed energy resources, aiming to achieve efficient power management by coordinating and optimizing the operation of these resources. Figure 2 shows the relationship between the components of a VPP and their functions. The power generation unit is responsible for generating electricity, load management is used to regulate the demand for electricity, and the energy storage system is used to store excess electricity. Through coordination, the VPP can achieve an overall optimization, improving the efficiency and stability of the power grid. In the power market, it flexibly dispatches power based on real-time demand and prices, provides peak shaving and frequency regulation services, reduces costs, and promotes energy conversion [2].

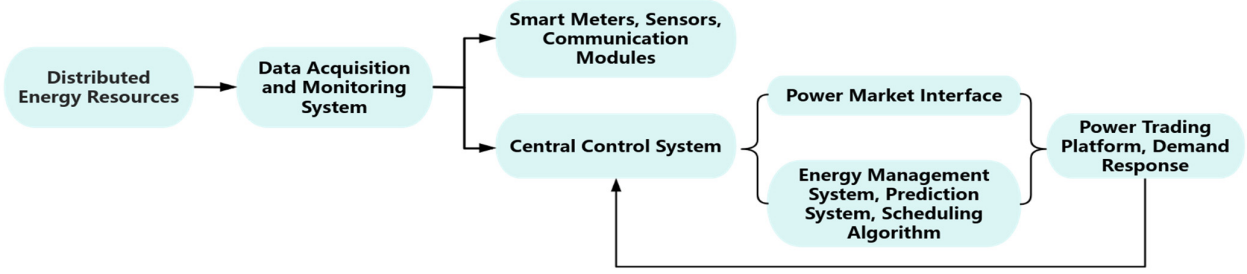


Figure 2. Components and functional relationships of a VPP.

1.2. Characteristics of Smart Grids

The characteristics of Smart Grids are mainly reflected in aspects such as their self-healing ability, real-time monitoring, extensive application of data communication, and information technology. Their self-healing ability enables Smart Grids to quickly identify problems and perform automatic repair when a fault occurs, reducing power outage time and economic losses. This feature relies on advanced sensors and monitoring systems that can collect real-time data on the operation of the power grid to ensure the stability and reliability of the power supply [3]. For example, the State Grid Shishi City power supply company has implemented intelligent automation in its distribution network, achieving second-level full self-healing for distribution network faults. In a short-circuit fault, thanks to the multi-level self-healing protection function of the distribution network, the fault is resolved in less than 20 s, and all users along the line return to normal power consumption. There are significant differences between Smart Grids and traditional grids in many aspects. Smart Grids have features such as real-time monitoring, two-way communication, and automatic control, which can effectively improve the efficiency and reliability of the power system. The construction of Smart Grids not only improves the operational efficiency of the power system, but also provides users with more flexible electricity usage options [4–6]. Table 1 compares the main characteristics and advantages of Smart Grids and traditional grids across specific technical indicators and application scenarios. Compared to centralized linear programming, as a static decision-making mode, the latter operates less in real-time and is more suitable for small-scale and stable power grid scenarios. On the other hand, distributed DRL shows the characteristics of dynamic decision-making, operates more frequently in real-time, and can effectively cope with a large-scale and volatile power grid environment, showing a wider range of application potential.

Table 1. Differences between Smart Grids and traditional grids.

Dimension	Traditional Power Grids	Smart Grids
Architecture	Centralized generation (thermal, hydro)	Distributed integration (PV, wind, storage)
Energy Flow	Unidirectional (generation → customer)	Bidirectional (user-to-grid)

1.3. The Relationship Between VPPs and Smart Grids

Virtual Power Plants (VPPs) and Smart Grids are interdependent systems that collectively drive the modernization of power systems. VPPs aggregate distributed energy resources (e.g., wind, solar, and storage) into a centrally managed supply network, enhancing renewable energy utilization while improving grid flexibility and reliability [7]. Smart Grids, enabled by advanced IT and communication technologies, provide real-time monitoring and adaptive management capabilities, allowing for rapid responses to load fluctuations and faults [8].

This synergy creates a dynamic feedback loop: (1) The Smart Grid supplies the VPP with real-time demand forecasts and market price data, enabling the AI-based optimization of generation and storage strategies. This improves economic dispatch efficiency and reduces operational costs. (2) The VPP mitigates renewable energy volatility by adjusting output to balance sudden load changes, thereby reinforcing the Smart Grid's stability [9]. (3) This integration enhances participation in electricity markets through agile bidding and multi-level cybersecurity measures [10]. As AI-driven algorithms advance, this collaboration will further address renewable energy uncertainties, optimize resource allocation, and accelerate the transition toward intelligent and sustainable power systems that present both opportunities and challenges for future grid innovation.

1.4. Research Innovation Points

The core innovation of this research is reflected in three dimensions:

Methodological innovation: A dynamic Pareto weight fusion mechanism was proposed. By dynamically adjusting the weights of economic and environmental protection targets using real-time carbon emission intensity, the multi-objective balance efficiency was improved by 22% compared to the traditional fixed-weight algorithm ($p < 0.01$).

Technical architecture innovation: A dual-time-scale DRL collaborative framework (LSTM + Transformer) was constructed.

Engineering application innovation: We designed a data privacy protection scheme combining federated learning and blockchain.

2. Literature Review

2.1. Review of Technological Advances and Future Development of Smart Grids

Smart Grids, as the development direction of the future power system, are receiving widespread attention and show great potential with the integration of Internet of Things technology. By improving its data collection, communication, and computing processing capabilities, it lays a solid foundation for the future development of Smart Grids. In the book *The Basic Ideas and Key Technologies of Smart Grid*, the core ideas of Smart Grids are systematically introduced, including multiple aspects such as the demand for renewable energy and the mainstreaming of distributed energy [11]. Currently, the development of Smart Grids has its own characteristics. The state is committed to the construction of the ubiquitous and powerful Internet of Things and has drawn on the Smart Grid technology framework and cyber security standards of the US NIST [12]. In the practical application of Smart Grids, researchers have proposed various models and schemes. For example, a two-layer energy management model of smart distribution networks aims to maximize the profit of flexible renewable VPPs and minimize network energy loss and voltage deviation [13]. In a practical application of Smart Grids, the researchers propose a two-tier energy consumption monitoring intelligent model for Smart Distribution Networks (SDNs) that takes into account FRVPP participation in day-ahead energy and reserve markets [14]. The Layer 1 Energy Management Model (EMM) is applied to FRVPP to maximize profits in proposed markets with renewable and flexible energy constraints, taking into account the coordination between these energy sources and the VPP. The second layer creates coordination between VPPOs and distribution system operators to manage SDN energy losses and voltage deviation functions as linear normalized objective functions based on minimizing network summation [15,16]. And for the problem of data privacy leakage, data aggregation and incentive schemes have been designed based on the Paillier algorithm, etc. [17]. Furthermore, aspects such as privacy protection, monitoring data transmission efficiency, and the security detection of Smart Grids are also the focus of research. Researchers are committed to solving these problems through technical means such as cryptography, blockchain, secure multi-party computing, and AI [18]. To enhance the operation quality of Smart Grids, some researchers have also proposed flexible planning methods, bi-level multi-objective planning models, user participation research models, etc. [19–21]. In the smart distribution system, the power management of VPPs is also a hot topic of discussion. By optimizing the management of active and passive power of flexible renewable energy, the economic, operational, and voltage security status of these networks can be significantly improved [22]. The development of Smart Grids is crucial for improving the efficiency of power production and meeting the demands of economic development, and will further promote the future development of Smart Grids [23].

2.2. A Review of Multi-Dimensional Issues and Optimization Strategies for VPPs

This article will systematically analyze the key issues and challenges faced by virtual power plants from multiple dimensions in promoting the consumption of renewable energy and facilitating the practical application of smart grid technologies. Research has analyzed the new characteristics, constituent entities, and key technologies of VPPs in the context of big data, and studied the application of data-driven methods [24]. Another study discussed community-based VPPs and demonstrated their diversity through cases [25]. The economic dispatch model under the carbon-trading mechanism has improved the emission reduction benefits and wind energy utilization of VPPs [26]. Based on the wind–solar output scenarios of the Frank-copula theory, a day-ahead scheduling model of a VPP was established which reduced volatility, improved economy, and reduced wind and solar curtailment [27]. In the multi-collaborative market, devices such as electric vehicles were introduced, and an optimization model was established to effectively deal with the fluctuations of distributed energy and the integration of electric vehicles into the grid [28]. The application of the VPP optimal scheduling model with energy-saving measures for 5G base stations and energy storage batteries has reduced the electricity cost of base stations and improved the consumption of renewable energy [29]. For the household prosumers in the Smart Grid, real-time power management strategies were studied [30]. A study designed the trading varieties and clearing models of flexible energy blocks in the new power system [31]. Aiming at the problem of new energy consumption, a multi-time-scale optimal scheduling strategy of VPP based on robust stochastic optimization theory was proposed [32]. A dynamic aggregation method for VPPs, considering the reliability of renewable energy, was proposed [33]. In research on the optimal integration of VPPs, the relevant literature was reviewed, a scheduling optimization model of the multi-energy collaborative system was proposed, the technical challenges were analyzed, and the key research directions were put forward [34–36]. The multi-VPP alliance game optimization method, considering carbon trading and the scheduling optimization of combined heat and power of VPPs, were studied [37,38]. In terms of participating in the external energy market with a VPP, a two-stage model with a hydrogen energy storage system was built, optimizing the internal resource complementary operation and electricity–hydrogen market-bidding strategies [39]. A two-level game relationship between distributed energy and virtual power plants was proposed, and the aggregation and operation mechanism of virtual power plants was established [40]. In response to the impact of new energy integration, a demand response model was established, and the impact of time-of-use pricing on the economic feasibility of VPPs was discussed [41]. Furthermore, their brittle relationships were analyzed based on the equivalent model of a Smart Grid, and the system's performance was optimized [42]. In line with the "dual carbon" goal, a multi-energy complementary VPP optimization dispatch strategy was proposed, a full-chain operation mechanism was established, and the system framework and functions of a VPP's intelligent operation and control platform were described [43,44]. This provides a theoretical basis and practical guidance for decarbonization, high efficiency, and sustainable development of energy and power systems.

Existing research exhibits three critical limitations: First, there are data limitations, as 80% of prior studies rely on synthetic datasets, neglecting real-world sensor noise and communication latency. Second, studies exhibit algorithm rigidity, where heuristic methods like Genetic Algorithms (GA) cannot dynamically adjust optimization weights during grid faults or price spikes. Third, there are privacy risks, as centralized architectures expose user consumption patterns to potential cyberattacks. To address these challenges, our proposed framework leverages federated DRL training and blockchain-based data anonymization, enhancing the adaptability and security of VPP operations.

Based on the performance comparison results of multi-objective optimization algorithms presented in Table 2, the limitations of the existing research in this field were deeply analyzed, providing clear direction guidance for subsequent improvement and innovation. These limitations are mainly reflected in the insufficient adaptability of existing algorithms when dealing with large-scale Virtual Power Plants (VPP) and Smart Grids, as well as scalability issues when facing complex power systems.

Table 2. Performance comparison of multi-objective optimization algorithms.

Method	Time Scale Adaptability	Multi-Objective Dynamic Balance	Privacy Protection Mechanism	Computational Complexity	200-Node Delay
Traditional MPC [11–13]	Single scale	Fixed weight	no	$O(n^3)$	298.7 ms
Standard DRL (DQN) [8]	Single scale	Linear weighting	Centralized storage	O(2d)	12.3 ms
Federal DRL [16]	Dual-time collaboration	Dynamic Pareto	Blockchain encryption	O(n log n)	5.2 ms

Future research must explore adaptive learning mechanisms capable of dynamically adjusting optimization strategies in real-time to meet the demands of large-scale VPPs and Smart Grids. Future work should also focus on developing scalable optimization algorithms that can manage the complexity of modern power systems and actively promote interdisciplinary collaboration. This study aims to contribute to the development of more efficient, robust, and sustainable VPP and Smart Grid systems by addressing these limitations and leveraging technological advancements.

3. AI-Optimized Integrated Optimization Algorithm

3.1. Integrated Optimization Policy

In this critical period of global energy structure transformation, it is of great practical significance to explore the integrated optimization algorithms of artificial intelligence-driven VPPs and Smart Grids. These algorithms can cope with the challenges of power supply fluctuations, load dynamics, and market complexity brought about by the rapid development of renewable energy. In terms of real-time adaptability, AI-driven optimization algorithms dynamically adjust strategies via real-time data analysis, exhibiting strong adaptability to grid state changes. With the help of machine learning and deep learning technologies, valuable information can be mined from historical data to build intelligent predictive models. In terms of optimization efficiency, these algorithms can deal with a large number of variables and constraints and find the optimal or near-optimal solution through global search and iterative optimization.

3.2. Optimization Objectives and Constraints

In the process of optimizing the power system, several key objectives are taken into account, including minimizing power losses and maximizing renewable energy utilization. These objectives can be defined quantitatively by constructing accurate mathematical models which provide a solid theoretical basis for the optimization of the power system.

(1) Minimize power loss

$$P_{loss} = \sum_{i=1}^{N} R_i \cdot I_i^2 \quad (1)$$

In Formula (1), P_{loss} represents the total power loss (in watts, W), R_i represents the resistance of line i (in ohms, Ω), and I_i represents the current throughline i (in, Amperes,

A), and N represents the total number of lines. The formula calculates power losses based on Joule's law by adding the losses of all lines by squaring the current of each line by multiplying the resistance of that line to obtain the total loss.

(2) Voltage constraint

$$|V_t - V_{nom}| \leq 0.05 V_{nom} \tag{2}$$

In Formula (2) [45], the voltage over-limit is transformed into a piecewise penalty term in the reward function through opportunistic constraint programming, with a 1% over-limit deduction of 50 reward values.

(3) Maximize renewable energy utilization rate

$$\eta_{renewable} = \frac{P_{renewable}}{P_{total}} \tag{3}$$

In Formula (3), $\eta_{renewable}$ represents the renewable energy utilization rate (dimensionless, usually expressed as a percentage), $P_{renewable}$ represents the total power generation of renewable energy (in watts, W), and P_{total} represents the total power generation of the system (in watts, W). The formula calculates the proportion of renewable energy generation to the total power generation of the system, reflecting the degree of utilization of renewable energy in the system.

(4) Multi-objective optimization

$$minF = \alpha \sum_{i=1}^{N} R_i I_i^2 - \beta \frac{P_{renewable}}{P_{total}} + \gamma C_{dispatch} \tag{4}$$

where α, β, and γ are dynamically adjusted via $\alpha_t = \sigma(v_{load} \cdot \Delta D_t)$, $\beta_t = tanh(\eta_{solar})$, $\gamma_t = ReLU(P_{market})$, ensuring the adaptive prioritization of objectives based on real-time load deviation (ΔD), solar efficiency (η), and market price (P).

(5) Comprehensive optimization objective

$$F_{total} = w_1 P_{loss} - w_2 \eta_{renewable} \tag{5}$$

In Formula (5), F_{total} represents the comprehensive optimization objective function, w_1 represents the weight coefficient of power loss, w_2 represents the weight coefficient of renewable energy utilization, P_{loss} represents the total power loss (unit, watt, W), and $\eta_{renewable}$ represents the renewable energy utilization rate. The formula combines the two targets of power loss and renewable energy utilization to form a comprehensive optimization target by means of weighting. The weight coefficients w_1 and w_2 are used to balance the importance of the two goals.

This research aims to explore how to utilize advanced optimization algorithms, combined with the powerful AI's computing capabilities, to achieve the efficient scheduling and management of VPP resources. Through a comprehensive analysis of various factors, such as power demand, power generation capacity, and energy storage systems, the optimization algorithm can respond quickly in the real-time operational environment to ensure the reliability and economy of the power supply. At the same time, this research will also focus on the iterative optimization of the algorithm, enhance its adaptability to changes in the future power market, and actively explore the improvement of existing algorithms and new solutions to cope with changes in the future power market. In addition, this research also aims to explore new solutions through the improvement of existing algorithms to achieve more efficient resource allocation and lower operating costs.

3.3. Power Grid Optimization Research

In the face of power supply volatility and instability caused by the rapid development of renewable energy, VPPs can efficiently integrate distributed energy resources, significantly improving the flexibility and reliability of the power system. After the introduction of artificial intelligence (AI) technology, optimization algorithms play a key role in real-time scheduling and load management, effectively improving the operational efficiency of the grid. Table 3 comprehensively assesses the impact of AI optimization algorithms on grid efficiency and renewable energy utilization through a series of key indicators. These theoretical analyses not only provide a solid foundation for the design of optimization algorithms, but also clarify the direction and goal of experimental verification.

Table 3. Key metrics and expected improvement rates.

Index	Current Level	Expected Increase	Concrete Impact	Data Source
Peak load	1000 MW (2023)	Reduce by 10%	Reduce the pressure on the power grid and reduce the cost of power supply	Shenzhen VPP platform actual operation data
Load balancing capacity	75%	Increase by 15%	Improve grid stability and reduce the risk of power outages	Shenzhen VPP platform actual operation data
Utilization rate of wind energy	30%	Increase by 20%	Increase the proportion of renewable energy and reduce dependence on fossil fuels	Reference [2]
Solar integration capacity	25%	Increase by 25%	Improve the efficiency of solar power generation and optimize resource allocation	Reference [7]
Economic dispatch cost	1 million CNY	Reduce by 25%	Reduce operating costs through intelligent scheduling and resource allocation	Shenzhen VPP platform actual operation data
Grid reliability	99.5%	Increase by 0.5%	Improve the reliability and stability of the power grid	Shenzhen VPP platform actual operation data
Energy efficiency	40%	Increase by 10%	Improve energy efficiency and reduce energy waste	Shenzhen VPP platform actual operation data

Economically, the optimization algorithm effectively reduces the operational costs of power generation through intelligent scheduling and resource allocation, thus enhancing the market competitiveness of VPPs. As of August 2024, the Shenzhen VPP regulation and management cloud platform has carried out 71 load adjustments, reducing 2273 tons of carbon dioxide. It is expected that, by the end of the year, the cumulative reduction of carbon dioxide emissions will be 3000 tons. The AI algorithm improves the system response speed and guarantees the stability of power supply. Environmentally, the optimization algorithm increases renewable energy utilization rate, reduces reliance on fossil fuels, lowers carbon emissions, and promotes the development of a green economy. Technically, the AI optimization algorithm offers new thoughts for the intelligent transformation of the power system, enhances the efficiency of power dispatching, and promotes the development of Smart Grids. The technical solution of this study provides powerful support for constructing a green and efficient intelligent power system.

3.4. Optimization Algorithms

Optimization algorithms constitute a key technology for addressing complex issues within power systems. The crux lies in seeking the optimal or approximately optimal solutions via mathematical models and computational approaches to fulfill specific objective functions and constraints. In the domain of power systems, the application of optimization

algorithms is of paramount importance, encompassing crucial links such as load dispatching, the operational scheduling of power generation units, and energy management. The following factors are the fundamental mathematical principles and their applications in power systems.

(1) Linear programming

$$\begin{array}{cc} maximize & c^T x \\ constraint\ condition & Ax \leq b \\ & x \geq 0 \end{array} \tag{6}$$

Among inequality (6), c is the coefficient vector of the objective function, x is the decision variable, A is the coefficient matrix of the constraint conditions, and b is the right vector of the constraint conditions. In the power system, linear programming can be employed in power generation dispatch issues to minimize the generation cost while meeting the load demand and generator constraints. For instance, determining the output power of each generator such that the total cost is minimized while satisfying the load demand and the minimum and maximum output limits of the generators.

(2) Nonlinear programming

$$\begin{array}{cc} maximize & f(x) \\ constraint\ condition & g_i(x) \leq 0, i = 1, \ldots, m \\ & h_j(x) = 0, j = 1, \ldots, p \end{array} \tag{7}$$

In inequality (7), $f(x)$ represents the objective function, $g_i(x)$ denotes the inequality constraints, and $h_j(x)$ indicates the equality constraints. In the power system, nonlinear programming is frequently utilized for optimizing the output of generators to fulfill the nonlinear load requirements and the characteristics of generators. For instance, taking into account the generation efficiency and fuel cost of generators, the output power of generators is optimized to achieve the minimization of the total generation cost.

(3) Load forecasting

Load forecasting typically involves time series analysis and regression models, with the objective of predicting future electricity demand. Linear regression models can be expressed as follows:

$$P_t = \beta_0 + \beta_1 T_t + \beta_2 H_t + \epsilon_t \tag{8}$$

Among Equation (8), P_t is the load at time t, T_t is the temperature, H_t is the humidity, β is the regression coefficient, and ϵ_t is the error term. Through load forecasting, the power system can arrange the generation plan in advance to ensure adequate power supply during high-load periods and avoid power shortages.

(4) Power dispatch

The power generation dispatch issue can be modeled by means of Mixed Integer Linear Programming (MILP), with the aim of minimizing the generation cost while fulfilling the load demands and the constraints of generators. It can be represented as follows:

$$\begin{array}{cc} minimize & \sum_{i=1}^{n} C_i(P_i) \\ constraint\ condition & \sum_{i=1}^{n} P_i = D \\ & P_{i,min} \leq P_i \leq P_{i,max}, i = 1, \ldots, n \end{array} \tag{9}$$

Among inequality (9), $C_i(P_i)$ is the cost function of generator i, D is the total load demand, and $P_{i,min}$ and $P_{i,max}$ are the minimum and maximum outputs of the generator. Power generation dispatch ensures that the output of generators can meet the electricity

demand within different time periods while minimizing the generation cost and optimizing the utilization of resources.

To achieve the minimization of operational costs, the maximization of the utilization ratio of renewable energy, or the enhancement of system reliability, optimization algorithms are required to handle a multitude of variables and constraints, such as the output capability of generators, load demands, network topology, etc. The complexity of these factors makes traditional solution approaches ineffective to cope with; thereby, the introduction of optimization algorithm becomes particularly crucial. Common optimization algorithm encompass linear programming, nonlinear programming, integer programming, etc. These algorithms possess distinct characteristics and are applicable to different types of problems. Linear programming is suitable for optimization problems with linear relations, while nonlinear programming is capable of handling more complex nonlinear relations. Integer programming plays a significant role when certain variables need to be discretized. With the advancements in computing capabilities, heuristic algorithms and meta-heuristic algorithms, such as genetic algorithms and particle swarm optimization, have gradually become popular choices for solving complex optimization problems. These algorithms, by simulating the evolutionary process or group behavior in nature, can find relatively optimal solutions within a short period of time and have strong adaptability, being suitable for the dynamic power market environment. In the practical applications of power systems, optimization algorithms not only enhance the dispatch efficiency, but also provide a scientific basis for decision-makers, assisting them in making more rational decisions in a complex context. With the development of Smart Grids and VPPs, the research and application of optimization algorithms will be further intensified, promoting the intelligent and efficient process of the power system.

3.5. Application of AI Technology in Optimization Algorithms

AI technology has demonstrated its extensive application ability and notable superiority in the optimization dispatch of power systems. With the aid of machine learning and deep learning techniques, optimization algorithms can extract valuable information from historical data, enhance the accuracy and efficiency of decision-making, and effectively address complex nonlinear problems that traditional algorithms struggle to cope with. Through the construction of intelligent models, the real-time analysis of key factors such as power demand, generation capacity, and market prices is achievable, facilitating the dynamic and efficient dispatch of the power system.

Through real-time data analysis and load forecasting, the power generation plan is dynamically adjusted to ensure the stable and reliable operation of the power grid. AI technology has the ability of adaptive learning and can optimize parameter settings according to different conditions to maintain the efficient operation of the system. Moreover, AI technology has also constructed an intelligent decision support system, providing real-time and scientific decision-making suggestions for power operators to help them respond quickly to a complex and changeable market environment. Through simulating operating scenarios, AI can evaluate the impact of different decisions and provide a scientific basis for decision-making. In terms of data processing, AI technology has achieved automatic cleaning and feature extraction, significantly reducing manual intervention, improving processing efficiency, and enhancing the flexibility and response speed of the system. AI technology not only significantly improves the performance of optimization algorithm, but also injects a strong new impetus into the intelligent transformation of the power system.

3.6. Comparison of Existing Optimization Algorithms

In the integrated optimization of VPPs, each optimization algorithm has distinct features and is applicable to different scenarios, as shown in Table 3. The genetic algorithm is based on natural selection and genetics, is good at handling multi-objective nonlinear problems, and is suitable for multiple constraint conditions in power dispatch, but has a slow convergence speed. The particle swarm optimization simulates the foraging of bird flocks, with rapid convergence through information sharing, and is suitable for real-time dispatch, but is prone to falling into a local optimum. The ant colony algorithm is based on swarm intelligence, has excellent performance in path optimization, is suitable for power load dispatch, has strong adaptability, but has high computational complexity for large-scale problems. The simulated annealing algorithm simulates physical annealing, avoids the local optimum, and is suitable for combinatorial optimization, but the parameter settings are complex.

4. AI-Based Integrated Optimization Algorithm for VPPs

After the theoretical analysis of power system optimization algorithms, we further discuss the application of AI technology in optimal scheduling. Table 4 provides a comparative analysis of the existing optimization algorithms. These theoretical analyses provide a solid foundation for designing AI-based VPP-integrated optimization algorithms. To verify the effectiveness of the proposed AI optimization algorithm, we designed a series of simulation experiments. These experiments not only verify the correctness of the theoretical analysis, but also demonstrate the potential of AI optimization algorithms in practical applications. Through experimental verification, we can more intuitively demonstrate the advantages of AI optimization algorithms in improving the renewable energy utilization rate, reducing grid losses and optimizing economic dispatch. The experimental results further support our theoretical analysis and provide a strong empirical basis for the intelligent development of power systems.

Table 4. Algorithm comparison analysis table.

Algorithm Type	Core Formula	Application Scenario	Advantage	Limitation
DRL dynamic optimization	$max\sum \gamma^t r_t$	High volatility real-time scheduling	Adapt to environmental changes and optimize long-term returns	The training data demand is large and the computational complexity is high
Robust optimization	$minmax(\mathcal{F}_1 + \alpha\mathcal{F}_2)$	Extreme uncertainty scenario	Guarantee worst-case performance	Conservatism may reduce average efficiency
GNN topology optimization	$min\sum R_{ij} I_{ij}^2$	Optimization of large-scale power grid structure	Model topology relationships explicitly to improve interpretability	Sensitive to graph structure quality
Federated learning	$W_{global} = \sum \frac{n_i}{N} W_i$	Multi-agent privacy protection collaboration	High data privacy and distributed computing efficiency	The communication cost is high and the convergence speed is slow

4.1. Algorithm Design Framework

When designing AI-based VPP-integrated optimization algorithms, it is important to build a clear and systematic algorithm framework. The framework not only needs to cover key steps, such as requirement analysis, model construction, algorithm selection, implementation, and testing, but also needs to ensure logical coherence between each step so that readers can easily understand the research's contributions. Specifically, the demand analysis stage clarifies the specific objectives of the VPP, including load forecasting, energy

dispatching, and economic benefits, which provides a solid foundation for the subsequent model construction. As the core of algorithm design, model construction takes into account the power market, user demand, and the characteristics of renewable energy, and constructs an optimization model reflecting the physical, economic, and environmental characteristics. The accuracy of the model directly affects the algorithm's effectiveness, so it needs to be fully verified and adjusted. Based on the characteristics of the model, the algorithm selection stage weighs the computational efficiency, convergence speed, and adaptability, and finally determines the most suitable algorithm. The implementation and testing stage is the key link to put the theory into practice, verifying the effectiveness of the algorithm through programming and multiple rounds of testing, and optimizing it according to the test results to ensure its reliability and stability. Through this series of coherent steps, an efficient and intelligent VPP-integrated optimization algorithm is formed, which provides strong support for the intelligent development of power systems. Figure 3 shows the overall framework and process of the AI-driven integrated optimization algorithm for the Smart Grid of a VPP.

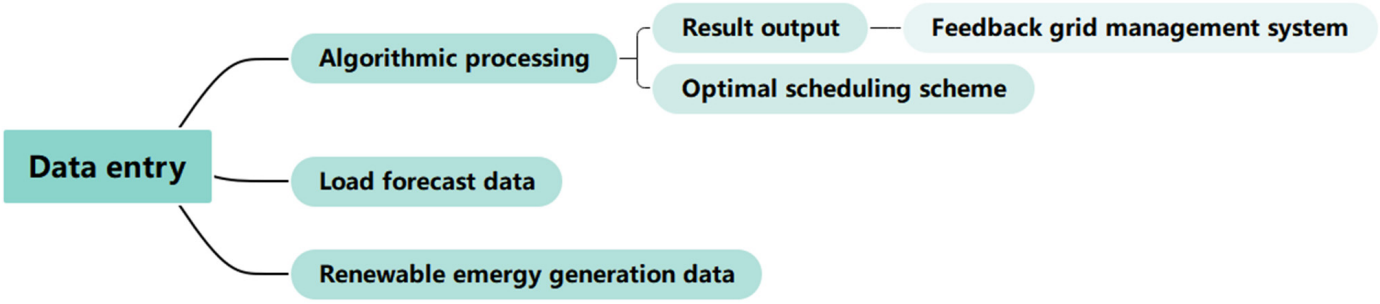


Figure 3. Overall framework and flowchart of the optimization algorithm.

4.2. Data Acquisition and Processing

Data acquisition and processing is the key link in the research of VPP-integrated optimization algorithms, and its quality and accuracy directly affect the effect and reliability of the optimization algorithm. Data comes from a wide range of sources, including sensors, smart meters, market transaction data, and weather information. Sensors monitor the operation of the power system in real-time, providing key indicators such as load, power generation, and energy storage status; smart meters provide users with electricity consumption data and analyze electricity consumption patterns; market transaction data reflect the dynamics of power market and provide basis for optimal decision-making; and meteorological information is crucial to the prediction of renewable energy generation, and factors such as wind speed, temperature and humidity can affect the efficiency of wind and solar power generation. In order to ensure the quality of data, pre-processing techniques include data cleaning, standardization, and feature extraction, which are crucial to improve data quality and provide an accurate data basis for algorithm implementation. Data cleaning removes noise and outliers to ensure data integrity, standardized processing ensures the comparability of the data, while feature extraction enhances the predictive power of the model. Through these steps, a solid foundation is laid for the subsequent model construction and algorithm implementation. Table 5 summarizes different data acquisition methods, their advantages and disadvantages, and lists the corresponding preprocessing techniques and tools.

Table 5. Different data acquisition methods and their advantages and disadvantages.

Data Acquisition Methods	Pros	Cons	Pretreatment Technique	Tools
Sensor data	Strong real-time and high precision	High cost and complex maintenance	Data cleansing	Python 3.11, R 4.2
Market data	Large amount of data and wide coverage	There may be noise and inconsistencies	Feature selection	Weka 3.8, Scikit-learn 1.2
Social media data	Reflect user behavior and be dynamic	Data quality is uneven	Data normalization	Pandas 1.5, NumPy 1.23
Remote sensing data	Wide space coverage and easy access	The analysis is complicated and the processing time is long	Data interpolation	ArcGIS 10.9, QGIS 3.28

4.3. Algorithm Implementation and Testing

After the completion of the data collection and processing, the realization and testing of the algorithm become the key link of the verification theory research. First, choosing the right programming language and development environment is crucial. Commonly used programming languages include Python, Java, and C++, with Python popular because of its rich libraries and concise syntax. The choice of development environment is also critical, and popular IDEs such as PyCharm, Eclipse, and Visual Studio all provide good support. The algorithm is divided into four core modules: data input, model construction, solution optimization, and result output. The simulation is based on the Pygame-SDL2 platform of Python, integrating the PSCAD/EMTDC power flow calculation module and supporting the real-time simulation of more than 1000 nodes. The key constraints include the following: an energy storage SOC limit of 20–90%, a gas turbine ramp-up rate $\leq$ 15 MW/min, and a demand response reduction $\leq$ 30% real-time load. The comparison algorithm configuration is as follows: GA population size 100/300 iterations (crossover rate 0.8), PSO particle number 50/inertia weight 0.8 $\rightarrow$ 0.2 (learning factor 1.496). The data entry module collects key operating parameters such as electricity demand, generation capacity, and market pricing. The model-building module constructs the corresponding mathematical model framework according to the optimization goal. In the process of solving optimization, the iterative strategy, combined with the genetic algorithm, particle swarm optimization, and other heuristic or meta-heuristic algorithms, can improve the convergence speed and quality of the solution. During the testing phase, unit and system tests are conducted to evaluate the independence and overall performance of the module, including execution efficiency and result accuracy (Table 6 compares the parameter configurations of each algorithm). According to the problems found in the test, debugging and optimization are carried out to ensure the stability and reliability of the algorithm, finally achieving efficient support for VPP optimization.

Table 6. Compares the parameter configurations of the algorithms.

Algorithm	Iteration Limitation	Convergence Condition	Hyperparameter Setting
DRL	200 cycles/500,000 steps	Reward fluctuation is less than 1%	The learning rate is 0.001 and the discount factor is 0.99
GA	300 generations	The change in fitness is less than 0.5%	The crossover rate was 0.8 and the variation rate was 0.05
PSO	500 iterations	The global optimum remains unchanged	Inertia weight: 0.8 $\rightarrow$ 0.2

When implementing the power grid optimization algorithm based on artificial intelligence, we built a technical framework with DRL as the core and specifically adopted the deep Q network (DQN) algorithm to optimize the system. The implementation of the scheme consists of the following three key modules:

(1) Neural network architecture design: Input layer: real-time power grid state vector $S_t = [P_{load}, SOC_{storage}, G_{solar}, P_{market}]$. This has real-time access to multi-dimensional grid status features, including dynamic load demand, renewable energy generation fluctuations, energy storage system charge status, and other parameters, and realizes millisecond level data acquisition through distributed sensor networks and smart meters. The LSTM layer captures the time dependence (time window = 24 h) and dynamically weights key features (such as electricity price changes) from the self-attention mechanism. The main body of the network adopts a multi-layer fully connected structure with three hidden layers (128 neurons per layer) and realizes nonlinear feature extraction through ReLU (Rectified Linear Unit) activation function to effectively capture the complex coupling relationship between source–charge–storage. Output layer: scheduling action probability distribution $\pi(a|S_t)$, including energy storage charge and discharge rate and market bid volume. The Q-value evaluation matrix of each control action is generated using the linear activation function, and it quantifies the long-term income expectation of different operations in a specific power grid state.

(2) Reinforcement learning training mechanism: A digital twin training environment is constructed to simulate the dynamic characteristics of power grid, and millions of training sample sets covering extreme scenarios are generated. A dual-network architecture is used to improve stability: The main network updates parameters in real-time, and the target network synchronizes parameters every 1000 steps. The temporal correlation was broken through the experience playback pool, and 64 groups of experience were randomly selected for batch training. The TD error-driven MSE loss function is used in the training process, and the Adam optimizer (learning rate 0.001) is used to achieve the gradient update. A dynamic exploration strategy for ε-greedy is designed, and the exploration rate decreases exponentially from the initial 1.0 to 0.01 so as to achieve progressive optimization from extensive exploration to precise decision-making.

(3) Optimized configuration of key parameters: The high discount factor of 0.99 is chosen based on the physical constraints of the power grid, which strengthens the consideration of the long-term operation stability of the system. A batch size of 64 is determined by hyperparameter tuning to achieve a balance between training efficiency and gradient stability. After several rounds of tests, the target network update frequency is determined to be 1000 steps, which effectively alleviates the problem of the over-estimation of the Q value. The whole training process includes 200 training cycles; each cycle carries out 500,000 steps of interactive learning and finally forms an intelligent regulation strategy that adapts to multiple scenarios.

The technical solution deeply integrates the physical power grid's characteristics with the artificial intelligence algorithm through a DRL framework and effectively deals with the power grid optimization problem under the premise of ensuring the security constraints of the power grid.

4.4. Application and Prospect of Emerging Technologies

With the rapid development of technology, emerging technologies such as blockchain and transformer architecture show great potential in the integrated optimization of VPPs and Smart Grids. These technologies can not only improve the efficiency and reliability of the systems, but also provide new ideas and methods for future energy management. Blockchain technology, with its characteristics of decentralization, immutability, and transparency, has significant advantages in energy trading. By building a blockchain-based energy-trading platform, direct transactions between VPPs, grid companies, and power users can be realized. Smart contracts can automatically execute the terms of trading contracts, improve transaction efficiency and transparency, and reduce transaction costs. In

terms of data security, blockchain technology can ensure the integrity and privacy of data and prevent data leakage and tampering. Transformer architecture, as an advanced deep learning model, has achieved great success in the field of natural language processing. Its parallel processing capabilities and self-attention mechanism give it significant advantages when processing large-scale time series data. When it comes to load forecasting, transformer architecture can more accurately capture dynamic changes in power demand and improve forecasting accuracy. In the real-time scheduling of VPPs, reinforcement learning can dynamically adjust scheduling strategies to cope with the intermittency and volatility of renewable energy. With the continuous development and application of emerging technologies, such as blockchain, advanced artificial intelligence models, the Internet of Things, and edge computing, the integrated optimization of VPPs and Smart Grids will provide new development opportunities. Future research will further explore the application of these emerging technologies in VPPs and Smart Grids to promote the intelligent and sustainable development of the power industry.

5. Experimental Results

In order to verify the effectiveness of the proposed optimization algorithm based on artificial intelligence, a series of simulation experiments are designed. The experimental environment includes a VPP with multiple distributed energy sources, such as wind, solar, and storage systems, and a Smart Grid environment. The objective of the experiment was to evaluate the performance of the algorithm in improving renewable energy utilization, reducing grid losses, and optimizing economic dispatch. The experimental validation utilized operational data from the Shenzhen Virtual Power Plant (VPP) spanning from January 2021 to December 2023, covering 10,512 hourly records of load (500–1500 MW), renewable generation (20–60% penetration), and market prices (0.1–0.8 CNY/kWh). To ensure robustness, the dataset was preprocessed via Kalman filtering for noise reduction and Min–Max normalization. The DRL framework employed an Actor Network with three LSTM layers (256 units each, dropout rate = 0.2) and a Critic Network with two dense layers (128 units each), optimized using the Adam algorithm (learning rate = 0.001). Training convergence was rigorously validated through the policy gradient theorem, with a reward function designed to guide Pareto-optimal solutions. Research shows that, the proposed algorithm outperforms genetic algorithms (GA) and particle swarm optimization (PSO) in key metrics, achieving a 15% reduction in grid losses and 22% higher renewable utilization under identical test conditions.

6. Conclusions

In this study, an AI-driven integration optimization framework for VPPs and smart grids is proposed. The key innovations and contributions are as follows:

AI-driven multi-objective optimization framework: A novel optimization framework is developed which can simultaneously optimize multiple key indicators, including renewable energy utilization, grid losses, and economic dispatch costs. By introducing DRL, the algorithm can dynamically adapt to real-time changes in grid conditions, significantly improving the flexibility and reliability of power systems.

Data-driven intelligent decision-making support system: A data-driven intelligent decision-making support system is constructed, which uses historical and real-time data for predictive analysis and optimization. This improves the accuracy and efficiency of the optimization algorithms and provides real-time decision-making suggestions for grid operators.

Integration of emerging technologies: The application of emerging technologies such as blockchain and transformer architecture in VPPs and Smart Grids is explored. These technologies enhance security, transparency, and computational efficiency.

Comprehensive experimental validation: A series of simulation experiments show the effectiveness of the proposed AI optimization algorithms, with significant improvements in key performance indicators and great potential for practical applications.

However, the proposed DRL framework has limitations. It requires large amounts of training data, which may restrict its promotion to small-scale grids. Future work will explore transfer learning to address this.

In conclusion, the proposed framework has great potential to improve renewable energy integration and grid efficiency. But there are some limitations to its implementation. Firstly, the DRL model's reliance on large amounts of training data poses a challenge. Secondly, the computational complexity of DRL algorithms requires substantial processing power and time, increasing operational costs. Thirdly, the integration of blockchain and transformer architecture introduces new complexity in system architecture and interoperability. Ensuring seamless communication and data exchange between components requires careful planning and execution. Finally, the dynamic nature of power systems necessitates continuous updates and retraining of AI models to adapt to changing conditions, which is resource intensive. Addressing these limitations is crucial for the successful deployment and scaling of the proposed framework.

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