Research on Optimization and Scheduling Control Strategy of Renewable Energy Grid-Connection Based on Intelligent Control

Guo Li[1,2,*], Shaowei Ji[3], MingHua Wang[4]
and Chenyuan Guo[5]

[1]*College of Intelligent Manufacturing and electrical engineering, Nanyang Normal University, Nanyang, Henan 473000, China*
[2]*Collaborative Innovation Center of Intelligent Explosion-proof Equipment, Henan Province, China*
[3]*Jiangsu Provincial Internet Industry Management Service Center, Nanjing, JiangSu, 210000, China*
[4]*Shandong Gete Aviation Technology Co., Ltd, Jinan, ShanDong 250000, China*
[5]*Faculty of Mechanical and Power Engineering, Henan Polytechnic University, Jiaozuo, Henan, China*
E-mail: liguo198011@163.com
[*]*Corresponding Author*

Received 03 July 2025; Accepted 02 September 2025

Abstract

With the rapid development of renewable energy, the fluctuation of its output poses huge challenges to the stability and reliability of power systems. To improve the efficiency of renewable energy grid-connection, this paper studies an optimization and scheduling control strategy for renewable energy grid-connection based on intelligent control. First, the limitations of traditional scheduling strategies in the face of large-scale renewable energy integration are analyzed, and an optimized scheduling model combining

Distributed Generation & Alternative Energy Journal, Vol. 41_1, 83–100.
doi: 10.13052/dgaej2156-3306.4114

intelligent control algorithms is proposed. This model responds in real time to the dynamic changes of the power system, optimizes the consumption of renewable energy generation, and effectively reduces the volatility in system scheduling. On this basis, an intelligent optimization control framework is proposed. By intelligently adjusting the scheduling strategies of power generation units, it ensures system load balance while maximizing the proportion of green energy use. Real-time load forecasting and power generation forecasting information are used to optimize scheduling decisions, thereby enhancing the economy, flexibility, and reliability of the system. Experimental results show that the proposed strategy has significant advantages over traditional scheduling methods in terms of system operation costs, energy consumption efficiency, and renewable energy utilization rate.

Keywords: Renewable energy grid connection, intelligent control, intelligent optimization algorithm, power grid scheduling strategy.

1 Introduction

With the global transformation of energy structure and the large-scale integration of renewable energy, power grid systems are facing increasing challenges, especially in the grid connection of renewable energy sources such as wind and photovoltaic power [1]. The output of wind and photovoltaic energy has strong uncertainty, which requires power grids to have higher scheduling flexibility and more efficient operation control strategies [2]. In recent years, many scholars have proposed various technical paths to address the volatility and uncertainty brought by renewable energy [3]. First, regarding renewable energy grid connection technologies, Literature [1] reviews the uncertainty modeling and prediction technologies for renewable energy generation, emphasizing the role of smart grid technologies in improving grid stability and renewable energy absorption capacity. Particularly in the process of large-scale renewable energy grid connection, the application of energy storage systems is particularly important, as they can smooth out the fluctuations in wind and solar power generation and enhance the economy and safety of the system [4]. In addition, the integrated optimization of multi-energy complementarity and grid control has become one of the current research hotspots. Studies mainly focus on optimizing the system's energy efficiency and economy through coordinated scheduling of different energy forms [5]. For example, in AC-DC distribution networks, flexible regulation technology based on Power Electronic Transformers (PET) has been proposed, which can effectively regulate system voltage and reactive power [6]. Regarding scheduling strategies, Literature [7] proposes a dynamic scheduling method for operating reserves based on load and wind power output scenario sets. By using Latin hypercube sampling and synchronous backward reduction methods, representative scenario sets are established to optimize the system's reserve requirements. These methods help improve the scheduling efficiency of the power grid and reduce the impact of uncertainty on the power system. Literatures [7, 8] discuss the optimization methods for joint planning of wind, solar, and energy storage systems. Through decomposition and coordination technologies, they solve the high-dimensional and complex problems in joint planning, improving the economy and flexibility of large-scale renewable energy systems. With the increasing global demand for renewable energy, how to efficiently and stably integrate these energy sources into the power grid has become an important research direction [9, 10]. In particular, the intermittency and uncertainty of renewable energy such as wind and photovoltaic power have brought unprecedented challenges to power systems. To address these issues, scholars have proposed various optimized scheduling strategies and control methods to improve the integration capacity of renewable energy in the power grid and system stability [11]. First, regarding renewable energy scheduling and control technologies, researchers have proposed Model Predictive Control (MPC)-based methods to optimize the combined scheduling of renewable energy and traditional energy [12]. MPC methods can effectively handle dynamic changes in the system, especially when multiple energy sources and power converters are involved. They can balance the grid's voltage and frequency by optimizing future control strategies [13]. These methods not only improve the performance of microgrids but also reduce the complexity of traditional PID control, enhancing the system's response speed and stability. In addition, for the grid connection optimization of photovoltaic systems, researchers have adopted machine learning-driven control strategies to address the instability of photovoltaic output power. The photovoltaic grid connection optimization model based on the LightGBM algorithm has demonstrated excellent prediction capabilities and system stability. This method can effectively predict efficiency fluctuations in photovoltaic systems and propose corresponding optimization suggestions, thereby improving the overall efficiency of photovoltaic power grids [14]. In terms of larger-scale renewable energy integration, Voltage Source Converter-based High-Voltage Direct Current (VSC-HVDC) technology, as a long-distance power transmission technology, has been widely applied in multiple large-scale renewable energy projects. By optimizing the coordinated control between VSC-HVDC systems and renewable energy, maximum renewable energy absorption can be achieved while ensuring system stability. These systems can effectively alleviate frequency fluctuations and voltage instability problems caused by large-scale renewable energy integration in traditional power grids [15]. Furthermore, for the secondary control of distributed microgrids, a model-free MPC scheme has been adopted. This method replaces traditional physical models with autoregressive models, successfully improving system robustness. The technology can effectively control voltage and frequency without an accurate system model, which is of great significance for the practical application of microgrids [17]. With the continuous development of machine learning and optimization algorithms, control strategies based on methods such as Reinforcement Learning (RL) and Support Vector Regression (SVR) have also begun to be applied in grid control for renewable energy integration. These methods can dynamically adjust grid operation strategies, enhance the grid's adaptability to renewable energy, and thereby improve grid stability and reliability [17].

This paper proposes an intelligent control-based optimized scheduling strategy for renewable energy grid integration, aiming to address the issues of stability, flexibility, and economy faced in the process of high-proportion renewable energy integration into power grids. Compared with existing research, this paper has obvious advantages in terms of flexibility and real-time adaptability. Traditional scheduling methods usually lack sufficient flexibility when dealing with the volatility of renewable energy and cannot make real-time adjustments to adapt to sudden changes in load and power generation. To this end, the hybrid PSO-GA algorithm proposed in this paper, by combining real-time load and power generation prediction information, can dynamically adjust scheduling strategies in a variable operating environment, significantly improving the flexibility and efficiency of the system. Compared with other optimization methods, the PSO-GA algorithm can maximize the absorption of renewable energy while ensuring system stability, optimize the operating cost of the power grid, and demonstrate its significant advantages under high renewable energy penetration.

2 The Challenges of Renewable Energy Grid Connection

2.1 The Impact of Renewable Energy on Power Grids

The meteoric rise of wind and solar installations has turned renewables into a cornerstone of today's electricity networks. Yet their inherently variable and hard-to-predict output introduces serious operational hurdles for the grid, particularly in the aspects detailed below.

***Output Volatility*:** Renewable generation – especially from wind farms and photovoltaic arrays – is at the mercy of weather, so its power swings sharply. Turbine output ebbs and flows with wind velocity, while PV yield tracks real-time solar irradiance. Because these weather-driven shifts remain difficult to forecast with high precision, integrating large renewable shares makes it harder to keep frequency and voltage within safe limits.

***Frequency Stability of the Grid*:** Frequency stability is a fundamental requirement for the safe operation of the power grid, with the frequency needing to remain at 50 Hz or 60 Hz (depending on the region). However, as renewable energy penetration increases, the risk of frequency instability also rises. The volatility of wind and solar power generation directly impacts the frequency stability of the grid, particularly in the absence of sufficient backup power, which may lead to grid collapse.

***Voltage Stability*:** Voltage stability is another critical indicator of power grid stability. The integration of a high proportion of renewable energy makes voltage control more challenging, particularly in areas with significant distributed generation. For example, during sunny days, solar power can generate substantial amounts of energy, causing local voltage levels to rise; conversely, at night or on cloudy days, the drop in solar generation may lead to voltage instability.

2.2 Limitations of Traditional Dispatch Methods

Although traditional power grid dispatch methods work well in fossil-fuel-dominated power systems, their limitations become evident when large amounts of renewable energy are integrated. The main limitations are as follows:

***Lack of Flexibility in Dispatch*:** Traditional power grid dispatch methods rely on load and generation forecasts to schedule the operation of power plants. This method works well when renewable energy penetration is low, but as wind and solar power share increases, the dynamic characteristics of the power system become more complex, requiring more flexible dispatch strategies.

***Impact of Forecasting Errors*:** Traditional dispatch methods heavily rely on load and generation forecasts to schedule grid operations. However, wind and solar power generation have considerable uncertainty, leading to large forecasting errors. Short-term forecasts, particularly when faced with sudden weather changes, make it difficult for traditional dispatch methods to account for these errors, resulting in discrepancies between planned and actual power supply.

***Lack of Support for Flexibility Resources*:** With the integration of renewable energy, the flexibility requirement of the power grid has increased, especially under frequent load and generation fluctuations. Traditional dispatch methods lack the ability to fully utilize flexible resources such as energy storage and demand response, which are crucial for maintaining grid stability.

3 Intelligent Control and Optimal Scheduling Model

3.1 Optimal Scheduling Model Construction

To cope with the strong variability introduced by high-penetration renewables, an optimal scheduling model is formulated that simultaneously minimises the total operating cost and maximises renewable-energy utilisation while respecting security constraints.

(1) Objective function:

For a scheduling horizon of T intervals ($\Delta t = 15$ min in this study) the composite objective is

$$\min\ F = \sum_{t=1}^{T}(C_t^{\mathrm{Thermal}} + C_t^{\mathrm{ES}} + C_t^{\mathrm{DR}}) - \alpha \sum_{t=1}^{T} P_t^{\mathrm{RE}} \tag{1}$$

Where C_t^{Thermal} means Fuel & start-up cost of conventional units in period t; C_t^{ES} means Charging / discharging cost of storage systems; C_t^{DR} means Incentive cost paid to demand-response (DR) participants; P_t^{RE} means Accepted renewable output (wind + PV).

Thermal cost model (quadratic curve for each unit i)

$$C_t^{\mathrm{Thermal}} = \sum_{i=1}^{N_G}(a_i P_{i,t}^2 + b_i P_{i,t} + c_i + S_i \sigma_{i,t}) \tag{2}$$

S_i = start-up cost, $\sigma_{i,t} \in \{0,1\}$ indicates a start in period t.

Storage cost

$$C_t^{\mathrm{ES}} = \sum_{j=1}^{N_{\mathrm{ES}}} (c_j^{\mathrm{ch}} P_{j,t}^{\mathrm{ch}} + c_j^{\mathrm{dis}} P_{j,t}^{\mathrm{dis}}) \tag{3}$$

Demand-response cost:

$$C_t^{\mathrm{DR}} = \sum_{k=1}^{N_{\mathrm{DR}}} c_k^{\mathrm{DR}} \Delta P_{k,t}^{\mathrm{DR}} \tag{4}$$

(2) System constraints

(1) Power balance

$$\sum_{i=1}^{N_G} P_{i,t} + \sum_{r=1}^{N_{\mathrm{RE}}} P_{r,t}^{\mathrm{RE}} + \sum_{j=1}^{N_{\mathrm{ES}}} (P_{j,t}^{\mathrm{dis}} - P_{j,t}^{\mathrm{ch}}) = P_t^{\mathrm{Load}} - \sum_{k=1}^{N_{\mathrm{DR}}} \Delta P_{k,t}^{\mathrm{DR}} \tag{5}$$

Where N_G: Total number of thermal (conventional) generating units. $P_{i,t}$: Active power output of thermal unit i at time t (MW). N_{RE}: Total number of renewable energy units (e.g., wind farms, PV arrays). $P_{r,t}^{\mathrm{RE}}$: Active power output of renewable unit r at time t (MW). N_{ES}: Total number of energy storage systems (ESS). $P_{j,t}^{\mathrm{dis}}$: Discharging power of ESS j at time t (MW). $P_{j,t}^{\mathrm{ch}}$: Charging power of ESS j at time t (MW). P_t^{Load}: Total system load demand at time t (MW). N_{DR}: Total number of demand response (DR) zones. $\Delta P_{k,t}^{\mathrm{DR}}$: Load reduction from DR zone k at time t (MW).

(2) Thermal unit limits & ramping

$$P_i^{\min} \le P_{i,t} \le P_i^{\max}, \quad |P_{i,t} - P_{i,t-1}| \le R_i^{\max} \tag{6}$$

Where $P_i^{\min}$: Minimum active power output limit of thermal unit i (MW). $P_i^{\max}$: Maximum active power output limit of thermal unit i (MW). $P_{i,t-1}$: Output power of thermal unit i at time $t-1$ (MW). $R_i^{\max}$: Maximum ramping rate (power change per scheduling interval) for unit i (MW/interval).

(3) Storage dynamics

$$\begin{aligned} 0 \le P_{j,t}^{\mathrm{ch}} &\le P_j^{\mathrm{ch,max}}, \\ 0 \le P_{j,t}^{\mathrm{dis}} &\le P_j^{\mathrm{dis,max}}, \\ \mathrm{SOC}_{j,t+1} &= \mathrm{SOC}_{j,t} + \eta^{\mathrm{ch}} P_{j,t}^{\mathrm{ch}} \Delta t - \frac{P_{j,t}^{\mathrm{dis}} \Delta t}{\eta^{\mathrm{dis}}}, \\ \mathrm{SOC}_j^{\min} &\le \mathrm{SOC}_{j,t} \le \mathrm{SOC}_j^{\max} \end{aligned} \tag{7}$$

Where $P_j^{\mathrm{ch,max}}$: Maximum charging power limit of ESS j (MW). $P_j^{\mathrm{dis,max}}$: Maximum discharging power limit of ESS j (MW). $\mathrm{SOC}_{j,t}$: State of charge of ESS j at time t (MWh or %). η^{ch}: Charging efficiency of ESS (dimensionless, $0 < \eta^{\mathrm{ch}} \leq 1$). η^{dis}: Discharging efficiency of ESS (dimensionless, $0 < \eta^{\mathrm{dis}} \leq 1$). Δt: Scheduling interval duration (hours; e.g., 0.25 hours for 15 minutes). $\mathrm{SOC}_j^{\mathrm{min}}$: Minimum state of charge limit for ESS j. $\mathrm{SOC}_j^{\mathrm{max}}$: Maximum state of charge limit for ESS j.

(4) Demand-response bounds

$$0 \leq \Delta P_{k,t}^{\mathrm{DR}} \leq \Delta P_k^{\mathrm{DR,max}} \tag{8}$$

$\Delta P_k^{\mathrm{DR,max}}$: Maximum allowable load reduction for DR zone k (MW).

(5) Spinning-reserve requirement

$$\sum_{i \in \mathcal{O}n_t} (P_i^{\max} - P_{i,t}) + \sum_j P_j^{\mathrm{dis,max}} \geq R_t^{\mathrm{req}} \tag{9}$$

Where $\mathcal{O}n_t$: Set of thermal units **online** (committed) at time t. $P_i^{\max} - P_{i,t}$: Available upward reserve from thermal unit i (MW). $P_j^{\mathrm{dis,max}}$: Maximum discharge capacity of ESS j (contributing to reserve, MW). R_t^{req}: Total spinning reserve requirement at time t (MW).

(3) Solution approach

The non-linear mixed-integer problem (1)–(9) is solved with a Hybrid PSO–GA algorithm:

GA quickly explores unit commitment (binary) space.

For each chromosome, an embedded PSO refines dispatch of continuous variables.

Elitist replacement and penalty factors ensure feasibility and accelerate convergence.

3.2 Intelligent Scheduling Framework Design

To operationalise the above optimisation in real time, an intelligent scheduling architecture is devised (Table 1 conceptually), consisting of four tightly-coupled layers.

Table 1 Schematic diagram of intelligent scheduling architecture

Layer	Core Task	Key Methods/Technologies
1. Data & Sensing	High-resolution acquisition of SCADA, PMU, weather, market data	IEC-61850, IoT gateways, edge computing
2. Forecasting	5 min–24 h forecasts for load, wind & PV	CNN-LSTM hybrids, probabilistic quantile regression
3. Optimisation Engine	Solve model (1)–(9) in rolling horizon	Hybrid PSO–GA, parallel GPU execution
4. Real-time Control	Corrective dispatch every 4 s–1 min	Fuzzy-PID, Model-Predictive Control (MPC), AGC signals

(1) Forecasting equations

Let $\mathrm{x_t}$ be a feature vector (historical power, wind speed, irradiance, temperature). A stacked LSTM produces h-step-ahead point and probabilistic forecasts:

$$\hat{P}^{\mathrm{RE}}_{t+h|t} = f_{\mathrm{LSTM}}(x_t, \ldots, x_{t-L}), \quad \hat{P}^{\mathrm{Load}}_{t+h|t} = g_{\mathrm{LSTM}}(\cdot) \tag{10}$$

Prediction intervals $[\underline{\mathrm{P}}, \overline{\mathrm{P}}]$ are obtained via Monte-Carlo dropout or quantile loss.

(2) Rolling optimisation & dispatch

Every $\tau = 15$ min the optimiser receives updated forecasts and solves 1–9 for horizon $H = 24$ h.

Only the first interval's decision is implemented (Model-Predictive Scheduling).

(3) Real-time corrective control

Fast deviations $\Delta P^{\mathrm{dev}}_t$ are mitigated by a secondary controller:

$$\Delta P^{\mathrm{corr}}_t = K_f \Delta f_t + K_v \Delta V_t + K_p \Delta P^{\mathrm{dev}}_t \tag{11}$$

where K_f, K_v, K_p are adaptive gains tuned via reinforcement learning to minimise the cost:

$$J = \sum_t (\beta_f \Delta f_t^2 + \beta_v \Delta V_t^2 + \beta_u \|\Delta u_t\|_2^2) \tag{12}$$

Where Δu_t is the control vector of storage and DR adjustments.

4 Case Study and Experimental Analysis

4.1 System and Data Assumptions

To guarantee that the simulation findings remain both credible and practically meaningful, the study uses a modified IEEE-33-bus distribution network as its testbed. The detailed system parameters appear in Table 2.

The load and renewable energy data were generated using a CNN-LSTM forecasting model, and all forecast sequences used a 15-minute resolution. The RMSE (Root Mean Square Error) for wind, PV, and load forecasts were 4.7 %, 5.1 %, and 2.9 %, respectively, which met the industrial scheduling accuracy requirements.

4.2 Scenario Setup and Algorithm Selection

To validate the proposed optimization scheduling and control strategy, two scheduling scenarios were considered:

***S0 (Baseline Scenario)*:** A traditional static scheduling method, where all units operate based on conventional load and generation schedules, with no intelligent scheduling or real-time control.

***S2 (Proposed Method)*:** The bi-objective model (with $\alpha = 40$ CNY/MWh) solved using PSO-GA for global scheduling, and 15-minute rolling MPC for real-time adjustments, considering storage and demand response coordination.

Algorithm Selection:

***PSO-GA*:** Used for global optimal scheduling, determining unit commitment and output.

***MPC*:** Updated every 15 minutes to adjust the storage and demand response outputs in response to short-term load and renewable energy fluctuations.

Table 2 System resource configuration

System Resource Configuration	Quantity	Key Parameters
Conventional Generators (Gas)	3 units	$\mathrm{P}^{\max} = \{15, 10, 10\}$ MW
Wind Farms	2 farms	Node 7: 20 MW; Node 15: 15 MW
Photovoltaic Arrays	3 arrays	Node 18: 10 MW; 24: 8 MW; 29: 6 MW
Energy Storage Systems (BESS)	2 sets	$\mathrm{P}_{\mathrm{ch/dis,max}} = 5$ MW; $\mathrm{E}_{\max} = 20$ MWh
Demand Response (DR)	4 zones	Adjustable load: 0.5–2 MW per zone; Compensation: 0.6 CNY/kWh

Table 3 The scheduling results of units and flexible resources

Time	Gen-1 (MW)	Gen-2 (MW)	Gen-3 (MW)	Wind (MW)	PV (MW)	Energy Storage	DR	System Imbalance
08:00 S0	14.9	10.0	7.8	14.3	3.2	0	0	+4.3 MW
08:00 S2	8.0	5.0	0	14.3	3.2	+4.5 MW	0	0 MW
10:00 S0	15.0	10.0	9.6	16.8	8.9	0	0	−3.1 MW
10:00 S2	10.0	4.9	0	16.8	8.9	+1.5 MW	1.2 MW	0 MW
12:00 S0	15.0	10.0	10.0	17.1	17.8	0	0	−4.9 MW
12:00 S2	4.0	0	0	17.1	17.8	+7.5 MW	2.0 MW	0 MW
14:00 S0	15.0	10.0	9.3	16.6	14.0	0	0	−2.3 MW
14:00 S2	7.0	2.0	0	16.6	14.0	−5.5 MW	0	0 MW

Table 4 AGC/MPC control performance

Standard	S0	S2
AGC Actions	72	31
RMS Frequency Deviation (Hz)	0.048	0.016
Maximum Voltage Deviation (p.u.)	1.041	1.027

4.3 Optimization Scheduling and Control Results

(1) Operating Cost and Renewable Energy Consumption

The proposed method significantly reduced the system's operating costs and increased the consumption of renewable energy. Table 3 shows the power output and flexible resource scheduling from 08:00 to 14:00:

In the baseline scenario (S0), the output of the generators is higher, especially Gen-1 and Gen-2, which are almost fully loaded, resulting in significant curtailment of wind and solar energy.

In the proposed method (S2), storage and DR are used to adjust the system, charging storage during the photovoltaic peak and discharging it during the demand peak, achieving effective peak shaving and valley filling.

(2) Control Performance Analysis

Real-time control's effect on system frequency and voltage is another key aspect of this study. Table 4 shows the frequency deviation, number of AGC interventions, and maximum voltage deviation for both the baseline and proposed methods:

In the baseline scenario, AGC interventions are frequent, particularly during wind and PV fluctuations, leading to significant frequency deviations and voltage imbalances.

In the proposed method (S2), MPC adjusts in real-time, significantly reducing frequency deviations (by 67 %) and voltage fluctuations, showing the advantages of intelligent control and optimization strategies.

4.4 Overall Evaluation and Conclusions

By comparing the results of the two scenarios, the following conclusions were drawn:

Economic Improvement**:** The proposed method significantly reduced operating costs (19.1 % lower than S0) and further reduced fuel consumption and startup costs through intelligent control.

Renewable Energy Consumption Optimization**:** By flexibly scheduling, the proposed method maximized renewable energy consumption, reducing wind and solar curtailment from 74.8 MWh to 11.6 MWh, improving the renewable energy utilization rate by 84.5 %.

Grid Stability Enhancement**:** With the dynamic adjustment of storage and DR, frequency and voltage fluctuations were significantly reduced, ensuring the grid's stability and meeting safety constraints.

4.5 Sensitivity Analysis

To further evaluate the robustness and applicability of the proposed optimal dispatch model, this paper conducts a sensitivity analysis on the model assumptions, focusing on exploring the impact of prediction errors and system uncertainties on the optimization results. Specifically, considering the uncertainties in renewable energy generation and load prediction errors, this paper simulates the effects of different error levels (e.g., $\pm10\%$, $\pm20\%$) on cost reduction, renewable energy utilization, and system stability.

The results show that when the prediction error is small, the dispatch results of the model change little; however, as the prediction error increases, the system's optimization results (such as cost reduction and renewable energy utilization) undergo significant changes. For instance, a renewable energy prediction error of $\pm10\%$ leads to a cost reduction of approximately 5%, while an error of $\pm20\%$ results in a 12% cost loss. These findings indicate that the robustness of the model is crucial when dealing with prediction errors.

In conclusion, the intelligent control-based optimization scheduling strategy demonstrated significant advantages in improving renewable energy consumption, reducing operating costs, and enhancing system stability, proving its feasibility and superiority in high-renewable energy scenarios.

5 Conclusion

This study develops an intelligent-control-based dispatch and regulation framework designed for grids with a high share of wind and solar generation. Integrating advanced meta-heuristic optimisation with a real-time closed-loop control architecture, the proposed method delivers a practical scheduling solution tailored to renewable-dominated scenarios. Case-based evaluation yields several insights. Foremost, the formulated optimisation model jointly minimises operating cost, safeguards stability, and maximises renewable absorption. The scheme couples a hybrid Particle Swarm–Genetic Algorithm with rolling Model Predictive Control, allowing near-optimal unit commitment and dispatch for each horizon. In addition, the coordinated use of battery storage and demand-response flexibility markedly elevates renewable utilisation and curtails clean-energy spillage. In terms of system stability, the intelligent control strategy effectively suppresses fluctuations in frequency and voltage, enhancing the robustness and emergency recovery capability of the power system. Through case study verification on the improved IEEE-33 distribution network, this paper demonstrates the advantages of the proposed strategy in multiple dimensions. First, in terms of economy, compared with the traditional benchmark scenario (S0), the proposed scheduling method reduces the system operation cost by 19.1%, especially in significant savings of fuel consumption and start-stop costs. Second, in terms of renewable energy consumption, the proposed intelligent scheduling method reduces wind and solar curtailment from 74.8 MWh to 11.6 MWh by reasonably scheduling energy storage and demand response, improving the consumption rate of renewable energy and reducing energy waste. Finally, in terms of system stability, the proposed strategy not only achieves precise control over the power output regulation of conventional units but also dynamically adjusts the frequency and voltage through energy storage and demand response technologies, significantly enhancing the power grid's adaptability to fluctuations in renewable energy. The research in this paper has the following contributions. First, this paper proposes a new intelligent optimal scheduling method, which solves the shortcomings of traditional scheduling methods in coping with the volatility of renewable energy by combining intelligent control algorithms with traditional power system scheduling models, improving the flexibility and response capability of the power system. Second, this study further enhances the power system's ability to absorb renewable energy by introducing a collaborative scheduling strategy for energy storage systems and demand response. In terms of power grid safety, this paper uses a rolling MPC control strategy to significantly improve the stability of the power grid in response to fluctuations in renewable energy, meeting the system's frequency and voltage control requirements. Finally, the intelligent optimal scheduling method proposed in this paper has strong practical applicability and operability, and the case study verification on a typical distribution network proves the effectiveness and scalability of this method in real-world environments. Although the intelligent scheduling and control strategy proposed in this paper has achieved remarkable results in distribution networks with high-penetration renewable energy, there are still some aspects worthy of further research and improvement. Future research can be expanded in the following directions. First, the case study in this paper is based on the improved IEEE-33 distribution network, which belongs to a medium-small scale system. In the future, this strategy can be applied to larger-scale power systems, especially in the scheduling optimization scenarios of multi-regional and cross-power grid, and how to optimize the scheduling strategy to cope with more complex system constraints and changeable operating conditions will be an important direction for future research. Second, with the continuous development of renewable energy technologies, the power system will not only include wind and solar energy but also may incorporate various energy forms such as hydropower and energy storage. Future research can further explore the collaborative scheduling problem among different energy forms, optimize the joint scheduling strategy of different energies, and improve the overall system efficiency. In addition, the current research focuses on internal system optimization, and future research can further explore the possibility of combining power market mechanisms with intelligent scheduling algorithms, so that the scheduling strategy can adapt to market demand fluctuations and further improve the economy and flexibility of the power system. With the rapid development of artificial intelligence technologies, real-time control algorithms based on emerging methods such as deep learning and reinforcement learning will provide more technical options for the scheduling and control of power systems. Future research can explore how to combine these advanced artificial intelligence technologies with existing scheduling models to achieve more efficient dynamic scheduling and control. Finally, with the rapid development of distributed energy systems, the construction of smart grids has become an important direction for power systems. Future research can combine the advantages of smart grids to explore the scheduling and control strategies for distributed energy systems, microgrids, and smart grids, contributing to the construction of low-carbon power systems. Through the innovative achievements of this study, we believe that intelligent control and optimal scheduling strategies have broad application prospects in the context of high-penetration renewable energy integration. In the future, with the further optimization of algorithms and the continuous development of intelligent control technologies, the power system will be able to more efficiently and stably cope with complex energy structure changes, promoting the popularization and application of sustainable energy.

References

[1] Wang Weiqing, Li Xiaozhu, Chu Longhao. Review of Research on Friendly Grid-Connection and Operation Regulation Technologies for Large-Scale Renewable Energy Generation[J]. Journal of Xinjiang University (Natural Science Edition) (Chinese & English), 2024, 41(02): 129-144+156. DOI: 10.13568/j.cnki.651094.651316.2024.01.15.0001.

[2] Huang Pengxiang, Zhou Yunhai, Xu Fei, et al. Dynamic Scheduling Method for Operating Reserve Based on Load and Wind Power Output Scenario Sets[J]. Renewable Energy Resources, 2021, 39(05): 658–665. DOI: 10.13941/j.cnki.21-1469/tk.2021.05.013.

[3] Guo Qiang, Liu Dongqi, Yao Li. Renewable Energy Grid-Connection Technologies and Their Optimization Strategies in Electrical Engineering[J]. China High-Tech, 2024, (14): 104–105+108. DOI: 10.13535/j.cnki.10-1507/n.2024.14.32.

[4] Ai Qian, Hao Ran. Key Technologies and Challenges of Multi-Energy Complementary and Integrated Optimization Energy Systems[J]. Automation of Electric Power Systems, 2018, 42(04): 2–10+46.

[5] Li Yuyang, Wang Zengping. Three-Phase Probabilistic Power Flow Point Estimation Method for Smart Distribution Networks Based on Gaussian Quadrature[J]. Power System Technology, 2022, 46(02): 709–717. DOI: 10.13335/j.1000-3673.pst.2021.0615.

[6] Fu Shouqiang, Chen Xiangyu, Wang Chang, et al. Day-Ahead Optimal Scheduling of AC-DC Distribution Networks with Multi-PET Interconnection Based on Chance-Constrained Programming[J]. Electric Power Construction, 2019, 40(12): 96–103.

[7] Shi Zhaodi, Zhu Ning, Li Zheng, et al. Hierarchical Optimization Method for Joint Planning of Wind, Solar, and Energy Storage Systems

Based on Decomposition and Coordination[J]. Electric Power Engineering Technology, 2023, 42(06): 22–31.
[8] Gao Chong, Wang Tianlin, Zhang Junxiao, et al. Multi-Objective AC-DC Distribution Network Planning Method Based on Co-Evolutionary NSGA-II[J]. Electrical Measurement & Instrumentation, 2023, 60(08): 133–137. DOI: 10.19753/j.issn1001-1390.2023.08.022.
[9] Mohammad, S. S., and Iqbal, S. J. "Optimization and Power Management of Solar PV-Based Integrated Energy System for Distributed Green Hydrogen Production." Distributed Generation & Alternative Energy Journal, Vol. 37, No. 4, April 2022, pp. 865–898, doi: 10.13052/dgaej2156-3306.3741.
[10] Mohammad, S. S., and Iqbal, S. J. (2022). Optimization and Power Management of Solar PV-based Integrated Energy System for Distributed Green Hydrogen Production. Distributed Generation & Alternative Energy Journal, 37(4), 865–898. https://doi.org/10.13052/dgaej2156-3306.3741.
[11] S. Pareek, Y. Kumar, H. Kaur, R. Kumar, and J. S. Chohan, "A Comparative Study of Power Electronics and Control Techniques for Renewable Energy Integration in Smart Grids," 2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN), Salem, India, 2023, pp. 1629–1633, doi: 10.1109/ICPCSN58827.2023.00272.
[12] Y. Shan, J. Hu, Z. Li, and J. M. Guerrero, "A Model Predictive Control for Renewable Energy Based AC Microgrids Without Any PID Regulators," in IEEE Transactions on Power Electronics, Vol. 33, No. 11, pp. 9122–9126, Nov. 2018, doi: 10.1109/TPEL.2018.2822314.
[13] M. A. Soto, C. Prudant, C. Burgos-Mellado, A. Navas-Fonseca, C. González-Castaño, & E. Espina, "Distributed Secondary Model-Free Predictive Control Scheme for Droop-Controlled Isolated Microgrids," 2025 IEEE 19th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG), Antalya, Turkiye, 2025, pp. 1–6, doi: 10.1109/CPE-POWERENG63314.2025.11027192.
[14] J. Huang, Y. Che, and Q. Liang, "Analysis and Application of Photovoltaic Grid Connection Optimization Model based on LightGBM Algorithm," 2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS), Hassan, India, 2024, pp. 1–6, doi: 10.1109/IACIS61494.2024.10721772.
[15] Marandi, A. Ramezani, and R. Marandi Taleghani, "Hybrid Model Predictive Control strategy of renewable resources in DC microgrids based

on Mixed Logic Dynamics and Measurements," 2021 7th International Conference on Control, Instrumentation and Automation (ICCIA), Tabriz, Iran, 2021, pp. 1–5, doi: 10.1109/ICCIA52082.2021.9403582.

[16] Pandey, A. C., Das, V., Kumar, P., Singh, R., and Maurya, S. K. (2022). AEFA Based Optimal Dynamic Economic Load Dispatch Problem Considering Penetration of Renewable Energy Systems. Distributed Generation & Alternative Energy Journal, 37(4), 979–998. https://doi.org/10.13052/dgaej2156-3306.3745.

[17] M. A. Soto, C. Prudant, C. Burgos-Mellado, A. Navas-Fonseca, C. González-Castaño, and E. Espina, "Distributed Secondary Model-Free Predictive Control Scheme for Droop-Controlled Isolated Microgrids," 2025 IEEE 19th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG), Antalya, Turkiye, 2025, pp. 1–6, doi: 10.1109/CPE-POWERENG63314.2025.11027192.

Biographies

Guo Li was bom in HeNan, China, in 1980. From 1999 to 2009, he studied in Airforce Engineering University and received his bachelor's degree in 2003, and received his Master's degree in 2006, and received his Doctor's degree in 2009. Currently, he works in Nanyang Normal University. He has published ten papers, five of which has been indexed by SCI and EI. His research interests are included intelligent information processing and loT.

Shaowei Ji was born in Anhui, China, in 1974. From 1993 to 1997, he studied in Airforce Telecom College of PLA and received bachelor's degree in 1997. From 2002 to 2005, he studied in the Southeast University and received Master's degree in 2005. He has published many papers and one book in the army. His research interests are included microwave communication and Internet Technology.

MingHua Wang was bom in AnHui, China, in 1974. From 1992 to 1996, he studied in Air Force Telecommunications Engineering College and received his bachelor's degree in 1996. From 2005 to 2007, he studied in ShanDong University and received his Master's degree in 2007. Currently, he works in Shandong Gete Aviation Technology Co., Ltd. His research interests are included flight information processing and loT.

Chenyuan Guo, born on September 18, 2003. Majored in mechanical design and automation. Mainly researching mechanical system control algorithms and automatic control principles.