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Multi-Objective Capacity Configuration Optimization of Hybrid Power Systems Based on Enhanced Differential Evolution Algorithm

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ABSTRACT

Scientific and reasonable configuration of the capacity of wind power, photovoltaic and energy storage systems in hybrid power system (HPS) is an important prerequisite to realize its comprehensive benefits and promote the development of new energy sources, and it is also a hotspot of current research. In this paper, we improve the multi-objective differential evolution algorithm for HPS multi-objective capacity allocation optimization, and dynamically adjust the differential evolution strategy through Q-Learning to realize the adaptive selection of variant strategies, so as to enhance the reasonableness and accuracy of the optimization results. The study constructs a mathematical model that takes into account the economic (net present value) and reliability (power supply shortage index) objectives, and builds a wind-optical-storage hybrid system using AC coupling to deal with the uncertainty of new energy output and load demand, and verifies the validity of the model and methodology through typical regional examples to provide decision support for the planning of new energy power systems.

Introduction

With the accelerated global transition in energy structure and the deepening implementation of the carbon peaking and carbon neutrality goals, renewable energy sources, especially wind and solar power, are progressively evolving from secondary to primary energy sources within power systems, witnessing a continuous increase in their penetration rate¹. This large-scale integration of renewables presents unprecedented opportunities to establish a clean, low-carbon, secure, and efficient modern energy infrastructure. However, the inherent intermittency, volatility, and unpredictability of wind and solar resources pose severe challenges to the secure and stable operation, cost-effective dispatch, and reliable power supply of electrical grids. Against this backdrop, scientifically sound capacity configuration for renewable-integrated power systems constitutes the critical link to ensuring their long-term reliability, economic efficiency, and environmental sustainability.

Traditional power system capacity configuration methodologies predominantly emphasize single-objective optimization, such as cost minimization or reliability maximization, or resort to oversimplified weighted-sum approaches for multi-objective scenarios. However, the planning and operation of integrated renewable power systems constitute a complex decision-making challenge characterized by multiple competing objectives, numerous constraints, and highly coupled variables. Decision makers must simultaneously balance economic metrics (including capital investment and operational expenditures),

technical reliability indicators (notably loss of power supply probability and expected energy not supplied), and sustainability targets (specifically renewable energy utilization rates and environmental emissions such as carbon reduction). These objectives frequently exhibit inherent trade-off relationships: aggressive reliability enhancement may precipitate prohibitive capital costs, whereas cost-centric strategies often undermine system stability and environmental performance. Consequently, identifying a satisfactory Pareto frontier solution that effectively reconciles these competing dimensions is imperative to enable sustainable grid evolution under high renewable penetration.

Recent research has advanced the optimization of hybrid renewable energy systems (HRES) through various methodologies. Dursun et al.² developed an algorithm for optimal selection of HRES components, demonstrating in Turkey that solar-hydro and solar-geothermal pairings significantly enhance capacity utilization (e.g., 10.83% to 36.86%). Akrama et al.³ combined HomerPro simulations with demand-side management for off-grid HRES, achieving 29% lower capital costs and 6.09% reduced energy costs while improving reliability. Bu et al.⁴ proposed an integrated system that combines wind / photovoltaic, thermal storage, CO₂ sequestration, and building heat, using underground saline aquifers to achieve 66,263 GJ storage capacity and 81.17% thermal efficiency, thus expanding operational flexibility to 200-700 MW. Bhagat⁵ optimized India's HRES using FNN and Chemical Reaction Optimization (CRO), which dynamically enhanced component synergy and reduced wind curtailment despite geographical limitations. Hu et al.⁶ introduce a chaotic dynamic inertia weight PSO (DIWCPSO) for thermal PV wind storage systems, leveraging the average complementarity index (ACI) to increase annual revenue by 13.04% and renewable utilization by 8.28% in Inner Mongolia. Guo et al.⁷ applied adaptive weight PSO to CSP-centric systems, identifying optimal configurations (6:1 capacity ratio, 800 MWh storage) under peak electricity pricing (\$0.047/kWh) in Xinjiang. Sunanda Hazra et al.⁸ contributed to Moth Flame Optimization (MFO) for nonlinear scheduling challenges. The scheduling advancements are performed by Wang et al.⁹ using Deep Reinforcement Learning (DDPG) with kernel density estimation to reduce coal costs by 14.1% and carbon costs by 16.3%. Hu et al.¹⁰ integrated CGAN forecasting with Dynamic Line Rating (DLR), increasing profits by 25.4% and reducing wind/PV curtailment by 5%. Gao et al.¹¹ formulated a hybrid dynamic economic emission distribution (HDEED) model solved by the Pelican Optimization Algorithm (POA-CS), reducing load fluctuations by 21% while raising renewable revenues by 22.40%. Liu et al.¹² implemented stochastic chance-constrained programming with carbon trading, curtailing emissions by 8.35% and total costs by 14.94% while reducing reserve requirements by 31.84%. The system evaluation studies by Wang et al.¹³ established a two-stage robust optimization framework (C&CG algorithm) validating energy storage's critical role in stability assurance over output enhancement. Liu et al.¹⁴ deployed Gray Wolf Optimizer with Chaos (GWOH) for HDEED, suppressing grid fluctuations to reduce costs by 4.52% and emissions by 11.84%. Collectively, these works demonstrate significant progress in mitigating intermittency and enhancing the techno-economic viability of multi-source renewable integration.

However, there is still room for improvement in the following aspects of existing research¹⁵: insufficient depth of multi-objective collaborative optimization, insufficiently detailed portrayal of complex nonlinear trade-off relationships among core objectives such as economy, reliability, environmental protection, etc., and lack of a systematic multi-objective optimization framework; uncertainty handling capability needs to be strengthened, as the high degree of uncertainty in the new energy output and load demand presents a higher demand for the robustness of the configuration scheme¹⁶. Existing methods still have limitations in dealing with multi-dimensional uncertainty and its impact on multi-objectives; the balance between model complexity and solution efficiency, high-precision models are often computationally burdensome, how to improve the efficiency of the solution of large-scale complex systems while guaranteeing the accuracy of the optimization is a problem that needs to be urgently solved; the synergistic configuration of emerging elements (e.g. multiple types of energy storage, demand response) is not sufficiently taken into account, and the role of the energy storage system and the flexible load in energy storage systems and flexible loads play a significant role in smoothing fluctuations, improving consumption and improving flexibility, and their synergistic optimal allocation model with power capacity needs more in-depth research.

To address the above challenges, this paper focuses on the multi-objective optimization of capacity allocation for new energy power systems. The purpose of this study is to construct a multi-objective optimization mathematical model for the allocation of capacity for new energy power systems, taking into account the main objectives of economy (total investment and operating cost), reliability (power supply shortage index), and environmental protection (carbon emission). The model will detail key components such as wind farms, photovoltaic plants, energy storage systems (e.g., battery storage), conventional backup power sources when necessary, and grid connections. An efficient multi-objective optimization algorithm is designed and applied, and Q-Learning is applied to improve the variance strategy of the multi-objective differential evolutionary algorithm, in order to efficiently solve this high-dimensional, nonlinear, uncertainty-containing, and complex optimization problem, and to obtain the well-distributed Pareto optimal frontier, which clearly demonstrates the trade-offs between different objectives. Effective strategies are proposed to deal with the uncertainty of new energy output and load demand (e.g. using the typical scenario method, opportunity-constrained planning, or robust optimization methods) to enhance the robustness and practicality of the allocation scheme. The effectiveness of the proposed models and methods is verified by simulation analysis of a typical regional example system. The performance of the objective values and their interrelationships under different configuration scenarios are deeply analyzed to provide decision makers with diversified sets of preferred scenarios and scientific decision support.

The research results in this paper are expected to provide theoretical basis and methodological support for the planning, design and investment decision-making of new energy power system, to promote the synergistic optimization of the system in cost-controllable, reliable and environmentally friendly dimensions, and to help the construction of a new type of power system and the smooth realization of the national goal of “double carbon”.

Problem formulation and preliminaries

Hybrid power system modes

Individual renewable energy sources exhibit significant stochastic volatility in power generation, while integrating multiple complementary renewables can substantially mitigate aggregate output fluctuations by leveraging their inherent synergies. Wind and solar resources demonstrate pronounced diurnal and seasonal complementarity: solar irradiance peaks during daylight hours

when wind speeds typically subside, while nocturnal periods feature heightened wind activity amid absent solar generation; seasonally, solar availability predominates in summer months while wind resources intensify during winter. Taking advantage of these spatiotemporal patterns, hybrid power systems (HPSs) that integrate wind turbines, photovoltaic arrays, and energy storage devices achieve superior grid-compatible power delivery compared to standalone wind or solar installations. This synergistic integration not only yields smoother aggregate power output but also relaxes stringent technical-economic specifications for storage components, thereby enhancing system feasibility under decarbonization agendas.

Hybrid Power Systems (HPS) offer multiple architectural configurations, with the AC-coupled approach being selected for this study due to the predominance of AC-output wind turbines and their substantially larger capacity relative to photovoltaic units, incorporating battery storage as the primary energy buffer. As illustrated in Figure 1, the grid-interconnected HPS enables bidirectional power exchange with the main grid: during generation shortfalls, the system imports electricity through tie-lines to ensure load satisfaction, whereas during production surpluses, excess power beyond local demand is exported to the grid. Should persistent overgeneration continue after fulfilling both local consumption and export capacity, strategic wind or solar curtailment protocols are activated to maintain grid stability while optimizing resource utilization within technical constraints.

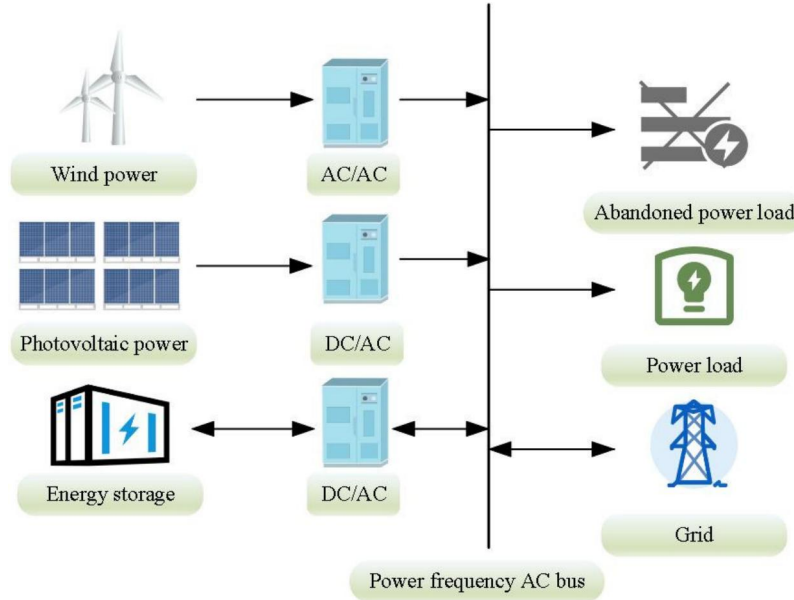


Figure 1. Caption Hybrid power system

Lifecycle cost assessment incorporates multiple economic representations, with the present study adopting discounted cash flow analysis to compute stakeholders' lifecycle payments via annualized cost-benefit streams. Time series modeling characterizes the operational behaviors of wind power, photovoltaic generation, battery storage, and load demand, where the respective power states at time t are indicated as $p_w(t)$, $p_s(t)$, $p_B(t)$ and $p_d(t)$. The calculation methodology for wind turbine systems exemplifies this approach, integrating both revenue inflows and expenditure outflows within a unified economic framework for the life cycle.

1) Annual Electricity Sales Revenue:

Recall that the wind speed at time t is $v(t)$, it is experimentally verified that the output force of the fan at moment t and the wind speed satisfy the nonlinear relationship between the foot:

$$P_W(t) = \begin{cases} 0 & v(t) < v_i \text{ or } v(t) \geq v_o \\ P_W \frac{v(t)-v_i}{v_r-v_i}, & v_i \leq v(t) \leq v_r \\ P_W, & v_r < v(t) < v_o \end{cases} \quad (1)$$

where, $v(i)$ is the cutoff speed of the wind turbine, $v(o)$ is the cutoff speed, is the rated wind speed, and t is the time in hours. Considering the load demand of the HPS, the power level of the storage battery and the transmission of power to the larger grid, the maximum deliverable power of the wind power system at time t is

$$P_{\max}(t) = P_d(t) + P_B - p_B(t) + P_i^{\max} \quad (2)$$

where, $P_B - p_B(t)$ is the maximum power that can be absorbed by the storage battery, $P_i^{\max}$ is the transmission capacity of the contact line, and the excess power of the HPS is calculated as the difference between the total system generation and the

maximum power that can be consumed:

$$P_{\text{MAR}}(t) = p_W(t) + p_S(t) - P_{\max}(t) \quad (3)$$

Since excess power is consumed by abandoned loads and does not bring any benefit, it is derived that the power sold $P_{WSEL}(t)$ by wind power at moment t is:

$$P_{WSEL}(t) = \begin{cases} p_W(t), & P_{\text{MAR}}(t) \leq 0 \\ \frac{p_W(t)P_{\max}(t)}{p_W(t)+p_S(t)}, & P_{\text{MAR}}(t) > 0 \end{cases} \quad (4)$$

The sum of the above yields an annual revenue from the sale of electricity from wind power:

$$I_{WSEL} = \sum_{t=1}^T (1 + \alpha)R(t)P_{WSEL}(t) \quad (5)$$

where $R(t)$ is the real-time tariff and α is the government-subsidized tariff factor.

2) **Annual The annualized investment cost model for wind power systems is formulated as follows:**

$$C_{WINV} = \frac{P_W U_W r (1 + r)^{L_W}}{(1 + r)^{L_W} - 1} \quad (6)$$

where r is the discount rate, L_W is the lifetime of the turbine, and the cost per unit power of the turbine is U_W .

3) **Annual Annual Outage Compensation Cost:** In scenarios where load shedding occurs due to power supply deficits, affected consumers receive compensation proportional to the undelivered energy. The outage power at time t denoted as $P_{EENS}(t)$ during such deficit events as:

$$P_{EENS}(t) = \begin{cases} 0, & \Delta P(t) \leq P_l^{\max} \\ \Delta P(t) - P_l^{\max}, & \Delta P(t) > P_l^{\max} \end{cases} \quad (7)$$

When load shedding occurs, compensation proportional to the undelivered energy is required. Let $k(t)$ denote the compensation rate per unit of outage energy, defined as 1.5 times the price of electricity in real time, as stipulated in relevant regulatory agreements. The total outage compensation cost is allocated proportionally to each generation source based on installed capacity. The compensation cost attributed to the deficiency in wind power is calculated as follows:

$$C_{WEENS} = \frac{C_{EENS} P_W}{P_W + P_S + P_B} \quad (8)$$

4) **Annual Grid Electricity Purchase Cost:** During system power deficits, electricity imported from the main grid incurs costs allocated pro rata to each component based on installed capacity. The annual grid purchase cost attributable to wind power is calculated as:

$$C_{WPUR} = \frac{f(P_g(t)) P_W}{P_W + P_S + P_B} \quad (9)$$

5) **Annual scrapping revenue:**

$$I_{WD} = \frac{P_W D_W r}{(1 + r)^{L_W} - 1} \quad (10)$$

where D_W is the end-of-life revenue per unit of power of the wind turbine, which is converted to the annual end-of-life revenue for one year of the operation period as I_{WD} .

6) **Annual O&M cost:** Noting that the annual O&M cost per unit of power of the turbine is M_W , the annual O&M cost is derived:

$$C_{WOM} = P_W M_W \quad (11)$$

The final result is a payment for wind power of I_W

$$I_W = I_{WSEL} + I_{WD} - C_{WINV} - C_{WOM} - C_{WEENS} - C_{WPUR} \quad (12)$$

Subsequent payment-related fees and revenues for PV power generation and storage batteries are calculated in a manner similar to the above calculation of wind power, and the relevant calculation process is omitted here.

Multi-objective optimization model

The capacity optimization of Hybrid Power Systems (HPS) aims to maximize/minimize objective functions. This study establishes a multiobjective optimization model for wind-PV-storage planning, evaluating system performance through economic viability (Net Present Value, NPV) and operational reliability. The mathematical formulation is described below

Objective Function 1: Net Present Value (NPV)

Reflecting the net benefit of the life cycle, NPV integrates revenue streams and cost outflows.

$$I_E = \sum_{i \in \{W, S, B\}} (I_{iSEL} + I_{iD} - C_{iINV} - C_{iOM}) / (1 + r)^n \quad (13)$$

where I_{iSEL} was electricity sales revenue, I_{iD} was scrap income, C_{iINV} was annual investment expenses (converted into annuities), C_{iOM} was annual operating and maintenance expenses. The calculation formula has been provided in the previous text, r represents the discount rate, n represents the year.

Objective Function 2: Reliability Objective (I_R), consisting of two parts: the power outage compensation cost and the system power purchase cost. The specific expression was:

$$I_R = \sum_{i \in \{W, S, B\}} (C_{iEENS} + C_{iPUR}) \quad (14)$$

where C_{iEENS} was the cost of compensation for the power outage, C_{iPUR} was the cost of the electricity purchase, The smaller the value of I_R , the smaller the price the system pays to ensure reliable operation of the system, and the higher the reliability of the system.

The following is the restrictive condition.

Capacity Boundary Constraints: The capacity of each equipment for wind and solar storage must be within a reasonable range. Due to the limited installation sites and the capacity of the equipment being limited by the investment cost, the conversion efficiency of the photovoltaic panels, as well as the length of the blades of the wind turbine, the capacity constraints of the equipment are as follows

$$\begin{aligned} P_W &\in \Omega_W = [P_W^{\min}, P_W^{\max}], \\ P_S &\in \Omega_S = [P_S^{\min}, P_S^{\max}], \\ P_B &\in \Omega_B = [P_B^{\min}, P_B^{\max}] \end{aligned} \quad (15)$$

$P_W^{\max}, P_W^{\min}$ were the upper and lower limits of the capacity of wind turbines and photovoltaic power generation and energy storage batteries, respectively.

The resulting multi-objective optimization model for HPS power planning is shown in Eq:

$$\begin{aligned} &\max I_E(P_W, P_S, P_B), \min I_R(P_W, P_S, P_B) \\ &\text{s.t. } P_W \in \Omega_W \\ &\quad P_S \in \Omega_S \\ &\quad P_B \in \Omega_B \end{aligned} \quad (16)$$

Q-Learning improves multi-objective differential evolution algorithm

In the capacity allocation of a new energy system, the multi-objective optimization demand and algorithmic dependence present significant coupling characteristics. On the one hand, the capacity allocation needs to simultaneously balance the multidimensional objectives of economy (minimizing the whole life cycle cost), reliability (probability of insufficient power supply is lower than the threshold), environmental protection (maximizing carbon emission reduction), etc., and there is a strong non-linear conflict between the objectives, for example, although enhancing the energy storage capacity will enhance the power supply reliability, it will push up the initial investment cost, and it is difficult to accurately depict this kind of trade-offs due to the defects of subjective assignments in the traditional weighted summation method. The relationship. On the other hand, the stochastic nature of wind power, the volatility of load demand, and the time-varying parameters during the equipment life cycle require the algorithms to have the ability to dynamically deal with the uncertainties, while the traditional algorithms (e.g., NSGA-II) rely on the fixed-variance strategy, which is prone to fall into the local optimum or convergence inefficiency when dealing with dynamic constraints such as the wind speed-light coupling scenarios or the fluctuation of electricity price. In addition, capacity allocation involves multilevel constraints such as physical characteristics of equipment (e.g., wind turbine cut-in and cut-out wind speeds, PV panel conversion efficiency), power balance constraints, and site capacity limitations, which make it difficult for traditional algorithms to efficiently search for a feasible solution in a high-dimensional solution space with constraint-handling mechanisms. It is due to the strong dependence of capacity allocation on multi-objective cooperative optimization, uncertainty robustness, and complex constraints processing, which makes the improvement of multi-objective optimization algorithms inevitable. Through the introduction of the dynamically adjusted variance strategy of Q-Learning, to achieve the self-adaptive selection strategy, the Pareto frontiers of high-efficiency search and incremental learning of uncertainty scenarios, which can satisfy the needs of the allocation of new energy system capacity from 'single-objective optimization' to 'single-objective optimization'. "By introducing Q-Learning, we can realize adaptive strategy selection, efficient search of Pareto front, and incremental learning of uncertainty scenarios, which can meet the real demand of capacity allocation of new energy system from single-objective optimization to dynamic multiobjective decision-making.

In differential evolution algorithm, the basic operation steps include population initialization, mutation, crossover and selection processes, and there are multiple mutation strategies (DE/rand/1/bin, DE/best/1/bin, DE/rand-to-best/1, DE/best/2/bin, etc.) in the population mutation operation, and the selection of different mutation strategies has a significant impact. In multi-objective optimization, different mutation strategies may show different advantages in different stages of optimization, so a dynamic adaptive strategy selection mechanism is needed. The core of QMODE algorithm is to consider each mutation strategy as an action, and select the optimal mutation strategy according to the current state of the population through the Q-learning algorithm, so as to improve the search efficiency and optimization performance of the algorithm. The flowchart of QMODE algorithm is shown in Figure. As shown in Fig 2.

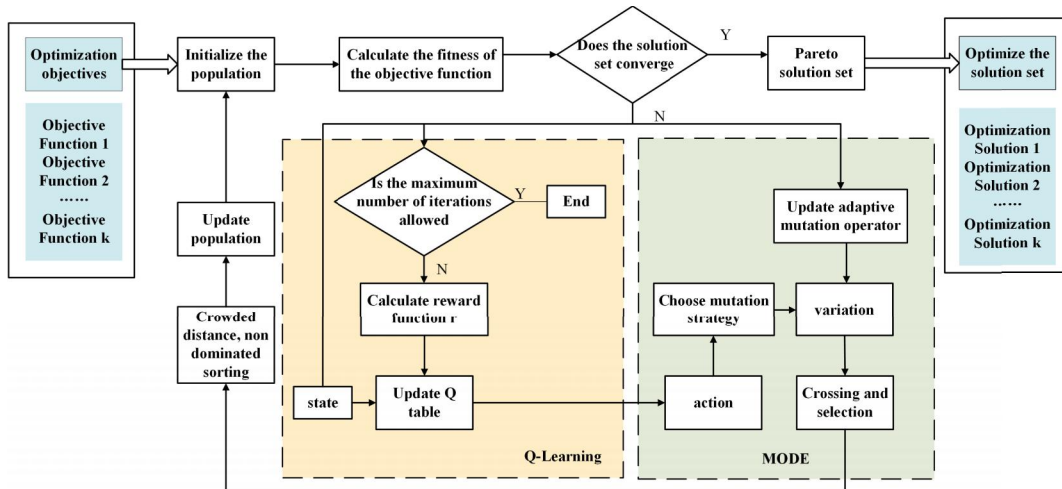


Figure 2. QMODE algorithm flowchart

1) **State characteristics:** in the QMODE algorithm, the state s needs to reflect the characteristics of the current population, and since the number of Pareto solutions obtained during multiobjective optimization is uncertain, the state s of the current population is defined as the average value of Pareto solutions in the current population:

$$s_t = \{F_1, F_2\} \quad (17)$$

where $F_i = \frac{1}{N} \sum_{j=1}^N f_i^j$, N is the number of Pareto solutions for the current population, f_i^j represents the value of the i th objective function for the j -th Pareto solution.

2) **Action selection:** in order to realize a dynamic and adaptive strategy selection mechanism, different variant strategies are defined as actions, and the action space contains the following variant strategies:

$$A = \{DE/rand/1/bin, DE/best/1/bin, DE/rand \rightarrow to \rightarrow best/1/bin\} \quad (18)$$

The specific expressions for each variation strategy are given below:

$$\begin{aligned} DE/rand/1/bin : \quad & v_{i,G+1} = x_{r1,G} + F \cdot (x_{r2,G} - x_{r3,G}) \\ DE/rand \rightarrow to \rightarrow best/1/bin : \quad & v_{i,G+1} = x_{i,G} + \lambda \cdot (x_{best,G} - x_{i,G}) + F \cdot (x_{r1,G} - x_{r2,G}) \\ DE/rand \rightarrow to \rightarrow best/1/bin : \quad & v_{i,G+1} = x_{i,G} + \lambda \cdot (x_{best,G} - x_{i,G}) + F \cdot (x_{r1,G} - x_{r2,G}) \end{aligned} \quad (19)$$

Where i denotes the sequence of individuals in the population, G denotes the number of evolutionary generations, $F \in [0.2]$ is a scaling factor, and $r1, r2, r3$ is a randomly selected individual with a different serial number than the population.

Action selection is done using the ϵ -greedy strategy, which is a method that balances exploration and utilization. In the ϵ -greedy strategy, an action ϵ is randomly selected with probability (exploration) and the action with the largest current Q value is selected with probability $1-\epsilon$ (utilization) with the following expression:

$$a_t = \begin{cases} \text{random}(A), & \text{if } \epsilon > \text{rand} \\ \text{argmax} Q(s_t, a_t), & \text{if } \epsilon \leq \text{rand} \end{cases} \quad (20)$$

3) **Reward function:** In multiobjective optimization problems, population quality and population diversity are two key factors. The quality of the population determines the merits of the solution, and the diversity of the population prevents the algorithm from falling into a local optimum. The reward function combines these two factors and is obtained by weighting changes in hypervolume (HV) and mean congestion distance (MCD) to balance their effects and improve algorithm performance. The calculation formula is as follows

$$r_t = \omega_1 \cdot \Delta HV_t + \omega_2 \cdot \Delta MCD_t \quad (21)$$

Where ΔHV_t denotes the amount of change in the hypervolume of the Pareto solution during the iteration process, and ΔMCD_t denotes the amount of change in the average crowding distance of the population, calculated as follows:

$$\begin{aligned} HV(P) &= \text{vol} \left(\bigcup_{i \in P} [f_i, r] \right) \\ MCD(P) &= \frac{1}{|P|} \sum_{i=1}^P \sum_{j=1}^m (f_{i+1}^j - f_{i-1}^j) \end{aligned} \quad (22)$$

where P is the number of Pareto solutions, f_{i+1}^j and f_{i-1}^j denote the two neighboring solutions of the i th nondominated solution, respectively.

4) **Q-table update:** The update of the action value function $Q(s_t, a_t)$ consists of the reward function r_t and the difference s_{t+1} between the maximum Q -value of the next state and the current Q -value.

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_t + \max_a Q(s_{t+1}, a) - Q(s_t, a_t)] \quad (23)$$

Results and discussion

The capacity allocation and optimal scheduling model of a multi-energy complementary energy system is simulated using the Enhanced Differential Evolution Algorithm (QMODE). Based on the multi-objective optimization analysis of the system's net present value and reliability, the study determines a comprehensive and optimal capacity allocation scheme for this system. The solar radiation in this area is particularly strong in spring and summer, especially in summer, and the light intensity distribution is intensive. Wind speed is relatively low in spring and summer, with maximum wind speeds not exceeding 15 m/s and usually staying below 10 m/s. In contrast, the wind speed increases significantly in fall and winter, with maximum wind speeds reaching 18 m/s. The wind speed and solar radiation intensity data for the whole year are shown in Fig. 3 and Fig. 4.

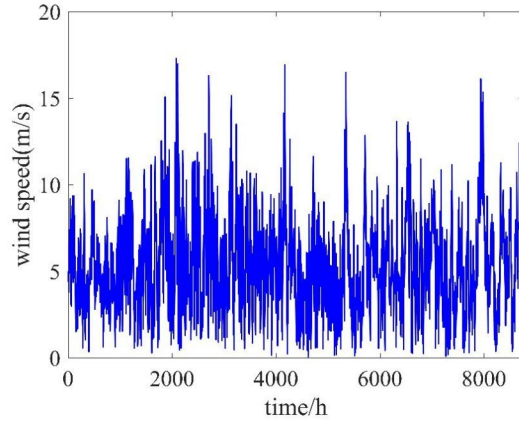


Figure 3. Annual wind speed

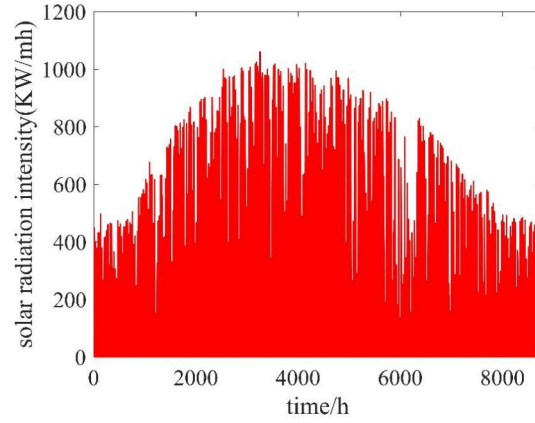


Figure 4. Annual schematic diagram of total solar radiation intensity

This article uses HDY-SMAD software for load simulation, fully considering building energy consumption, industrial activity energy consumption, production, living energy consumption, etc. The annual 8760 hour electricity load data is obtained as shown in Fig. 5.

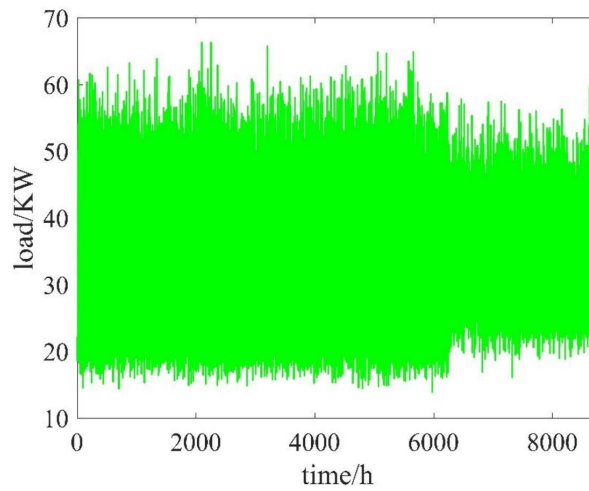


Figure 5. Annual electricity load

The main equipment includes photovoltaic generator sets, wind turbines, and energy storage units, with economic parameters as shown in Table 1. The parameter values for the optimization algorithm of QMODE are shown in Table 2.

Installations	Parameters	Values
Photovoltaic generator sets	Initial investment cost	2400 CNY/kW
	Operation and maintenance costs	0.03 CNY/kWh
	Life span	20 yr
Wind turbine	Initial investment cost	2800 CNY/kW
	Operation and maintenance costs	0.05 CNY/kWh
	Life span	20 yr
Energy storage	Initial investment cost	1050 CNY/kWh
	Operation and maintenance costs	0.08 CNY/kWh
	Life span	10 yr

Table 1. Main equipment economic parameters.¹⁷¹⁸

Different multiobjective optimization algorithms exhibit differential performance in optimizing the capacity configuration of wind solar storage hybrid power systems. According to the statistical data in Table 3, this conclusion can be drawn. QMODE demonstrates optimal economy in net present value (3.3089×10^{11} CNY) through adaptive mutation strategy, achieving the fastest convergence in 36 iterations, and the reliability (4.6932×10^6 CNY) is very close to the optimal MODE (DE/best/1) (only 2.3%), balancing profitability, reliability, and computational efficiency, making it suitable for engineering applications; Although MODE (DE/best/1) has the best reliability (4.5862×10^6 CNY), its economy and convergence efficiency are slightly inferior, making it suitable for scenarios with strict reliability requirements; MODE (DE/rand/1) and MODE (DE/rand best/1) have no outstanding performance in terms of economy, reliability, and convergence efficiency. Simple random or balanced mutation strategies are difficult to cope with the complexity of multi-objective optimization. In general, QMODE performs more evenly and is a better choice. If we focus on ultimate reliability, MODE (DE/best/1) can be considered, but other indicators need to be balanced.

Parameters	Values
Initial stock size	100
Maximum number of iterations	100
Probability of crossover	0.9
Probability of variation	0.1
Proportion of superior populations	0.3
Photovoltaic unit capacity allocation boundary	[0, 300]
Wind turbine capacity allocation boundary	[0, 300]
Energy storage unit capacity allocation boundary	[0, 800]

Table 2. QMODE algorithm optimization parameters.

Method	Net Present Value ($\times 10^{11}$)	Reliability ($\times 10^6$)	Iterations
QMODE	3.3089	4.6932	36
MODE(DE/rand/1)	2.8513	4.9521	45
MODE(DE/best/1)	3.2681	4.5862	39
MODE(DE/rand-best/1)*	2.9862	5.1181	52

Table 3. Optimization Result Data Statistics

Conclusions

This study addresses the multi-objective capacity optimization problem for Hybrid Power Systems (HPS), establishing an integrated economic-reliability model with dual objectives. Net Present Value (NPV) and system reliability (quantified through outage compensation and import costs from the grid). By dynamically adjusting mutation strategies in Differential Evolution (DE) algorithms via Q-Learning, adaptive optimization of the wind-PV-storage capacity configuration is achieved. Case studies demonstrate that the enhanced algorithm effectively handles renewable energy uncertainties, generating well-distributed Pareto-optimal solutions for typical regional scenarios, thereby providing diversified decision-making schemes for system planning.

Future research will focus on three dimensions: model expansion: Incorporating multi-type energy storage (e.g. compressed air) and demand response mechanisms to enhance operational flexibility. Uncertainty Quantification: Developing dynamic scenario-based optimization models using real-time meteorological data and electricity price volatility. Engineering Implementation: Creating grid-topology-adaptive optimization frameworks that address practical operational constraints (e.g., N-1 security, ramping limits) to support efficient planning of low-carbon power systems under the "Dual Carbon" goals.

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Author contributions statement

Jianguo Shi is responsible for the supervision and administration of the project, Qianpeng Hao conducted the simulation and experiment, Xinjian Wang was writing the original manuscript, Zhibin Jing reviewed the manuscript, Yan-Kai Zhu edited the manuscript, Qing-Kui Li is responsible for the revision and submission of the manuscript.

Competing interests

The corresponding author is responsible for submitting a [competing interests statement](#) on behalf of all authors of the paper.
The authors declare no competing interests.

Data availability

Data supporting this study are available in the supplementary materials via Baidu Cloud:
URL: <https://pan.baidu.com/s/1bhKgMRzsf9iOotYVxidIow?pwd=ksh1> Password: ksh1.

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