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Research Article

Economic dispatch model of renewable energy system considering demand response

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Abstract. Due to the intermittency and volatility of renewable energy, the system stability is poor and the operating cost is high. This study proposes an economic dispatch model for renewable energy systems based on a demand response model and differential evolution algorithm. A demand response model based on real-time flexible tariffs is combined with charging and discharging strategies for electric vehicles to optimize flexible load dispatch in the system. This combination is intended to improve the efficiency and reliability of grid operation. The traditional differential evolution algorithm is prone to getting stuck in local optima. Given this, this study introduces a deterministic sequence-improved differential evolution algorithm to enhance population diversity and local search ability, significantly improving the global search performance and convergence efficiency of the algorithm. To validate the effectiveness of the model, function extremum and system operation simulation experiments are designed. The results showed that the improved algorithm had a variance of 0 and an optimal value of 10^{-30} on multi-modal functions, and a variance of 0 and an optimal value of $10^{-3.5}$ on fixed dimensional functions. After considering demand response, the peak valley difference in electricity consumption between renewable energy systems A and B was 90.15MW and 527.55MW, with fluctuations of 36.57MW and 201.79MW, and operating costs of 46058.76 yuan and 52.3315 million yuan, respectively. Research findings indicate that the electric energy coordination and economic management of this model have been significantly enhanced. These enhancements effectively ensure efficient energy utilization, facilitate the safe and stable operation of the system, and provide a novel theoretical foundation for the optimization and scheduling of renewable energy systems.

Keywords: Demand response; Renewable energy; Electric vehicles; Economic dispatch; Determine the sequence; Differential evolution.

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1. Introduction

With the transformation of the global energy structure and the increasingly severe deterioration of the environmental climate, the utilization of Renewable Energy (RE) has become an important issue in the energy field. In the power system, the utilization rate of RE including wind and solar energy continues to increase, providing strong support for achieving green energy transformation. However, due to the intermittency and uncertainty of RE, its large-scale integration puts significant pressure on the economic dispatch of the Power System (PowS) (Osamn *et al.,* 2023). How to achieve optimal cost-effectiveness while ensuring stable operation of the PowS has become a key issue that urgently needs to be addressed. Yi *et al.* (2023) proposed a model-free economic scheduling method based on reinforcement learning to address the accuracy and stability issues of virtual power plants. By constructing a two-stage reinforcement learning framework to optimize training scheduling strategies, this method improved the robustness and safety of power output. Lei *et a*l. (2023) proposed a forward-looking economic dispatch strategy for wind power grid-connected systems to address safety issues caused by power fluctuations in the power grid. By dynamically climbing constraints and flexibly transferring loads to smooth power fluctuations, this strategy effectively improved calculation accuracy and efficiency. Liu *et al.* (2023) constructed a novel hybrid large-scale PowS economic dispatch method to enhance the power generation efficiency of the PowS. This method achieved local and global optimal scheduling by introducing gain sharing knowledge algorithm and differential evolution algorithm, and its search efficiency and robustness were significantly improved. Wang *et al.* (2024) proposed a multi-objective environmental Economic Dispatch Model (EDM) for PowSs to address the scheduling pressure. The optimal scheduling solution was obtained through an artificial bee colony algorithm and sequential preference technique. This model greatly reduced economic costs and pollution emissions. Nalini *et al.* (2024) proposed a PowS economic dispatch method based on an improved goose flame optimizer to solve the dynamic economic emission dispatch problem. By combining the goose flame optimizer with multi-objective algorithms to seek the optimal solution for dynamic economic scheduling problems, the accuracy and efficiency of this method have been improved. Despite the strides made by scientists in enhancing the safety and stability of the PowS through the investigation of economic dispatch, further research is necessary to ensure the optimal functioning of this critical infrastructure. However, existing economic dispatch methods still have shortcomings in handling dynamic dispatch demands and optimizing supply and

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demand and have a poor ability to cope with the volatility of RE and uncertainty on the demand side.

Demand Response (DR) constitutes a pivotal element of demand-side management in the PowS, wherein users are prompted to modify their electricity consumption patterns by implementing incentives or price signals. This approach has been demonstrated to exert a favorable influence on the promotion of equilibrium in electricity supply and demand, thereby ensuring the stable operation of the power grid (Yasmin *et al*., 2024). Luo *et al.* (2023) proposed a coordinated operation strategy for cogeneration microgrids considering DR to address the issue of household electricity utilization efficiency. By establishing a load DR model and a thermal inertia load model to coordinate power management, this strategy effectively reduced the operating costs of the system. Reka *et al.* (2023) developed a DR model built on user privacy to address power management issues in residential areas. This model used discounted random games and generative adversarial networks to analyze users' privacy needs, improving the efficiency of power grid operation and real-time analysis capabilities. Wynn *et al.* (2023) designed a distributed energy management system considering DR for the supply-demand balance of the PowS. The system applied an autoregressive moving average, Particle Swarm Optimization (PSO) algorithm, and DR program to achieve flexible scheduling of the current microgrid system, reduced peak load by 4.3%, and filled valley load by 5%. He *et al.* (2023b) suggested a DR prediction model grounded on multivariate loads to solve the energy planning problem in the PowS. The model used convolutional neural networks and gate loop units for load prediction. The data showed that the average absolute percentage error of the model has increased by more than 3%. He *et al.* (2023a) proposed a hybrid DR strategy for Electric Vehicle (EV) users' charging behavior, which guides users to make charging choices through dynamic time-of-use electricity pricing and incentive subsidy mechanisms. This strategy improved the adhesion of tram users and reduced the volatility of grid power. Martín-Ortega *et al. (*2024) proposed the Integrated Climate Action Mitigation Inventory Tool (MITICA). This proposal addressed the significant gap in defining emission reduction targets and reporting Greenhouse Gas (GHG)-related reporting elements in the process of developing Nationally Determined Contributions (NDCs) under the Paris Agreement. This initiative fostered uniformity among national GHG inventories, emission reduction strategies, and GHG projects. It further facilitated the optimization of tracking nationally determined contributions and the establishment of objectives in alignment with IPCC best practices. Additionally, it promoted the nexus between climate change and sustainable economic development. Nydrioti *et al.* (2024) addressed the significant impact of climate change on water resources. They proposed using Aquacycle software combined with the RCA4 Regional Climate Model (RCM) to simulate three climate emission scenarios (RCP 2.6, RCP 4.5, and RCP 8.5) to assess water demand and supply in the Aigeiros region of Greece over the next 30 years. This approach enables accurate prediction and optimization of water management strategies. Arabatzis *et al.* (2017) solved the problem of classifying Greek regional units based on the number and installed capacity of RE facilities. They proposed using hierarchical clustering analysis in multivariate statistical methods to enable detailed classification of the number and installed capacity of RE factories based on various regional units in Greece. Hosan *et al.* (2024) addressed the issue of research gaps concerning the impact of energy innovation funding on social equity in advanced economies. Utilizing a quantitative analysis, the researchers examined the direct and indirect effects of energy innovation funding on social equity through accelerated energy justice in 23 advanced economies from 1995 to 2020. Consequently, the necessity of a rational allocation and utilization of public energy innovation budgets for the promotion of clean energy technologies, the advancement of a just energy transition, and the enhancement of social equity, inclusiveness, and community participation was underscored. Many scholars' research have shown that DR can promote the optimization scheduling of RE and help balance the load of the power grid. However, there are still deficiencies in the incentive mechanism and benefit evaluation of current DR, which require further research and exploration.

In this context, this study proposes an EDM for Renewable Energy Systems (RES) considering DR. This study takes energy-saving and environmentally friendly EVs as the response object. It innovatively constructs an optimization scheduling model that comprehensively considers both the supply and demand sides. The model uses an improved Differential Evolution algorithm (DE) to seek the global optimal solution. It aims to achieve efficient optimization of supply and demand resources and smooth operation of the power grid, further promoting the sustainable development of the PowS.

The novelty of the study is mainly reflected in the combination of DR and DE algorithms to propose an EDM for RES. This model innovatively considers the user response behavior under real-time flexible tariffs and achieves integrated scheduling on both the supply and demand sides by optimizing the charging and discharging strategies of EVs. In addition, the Deterministic Sequence Differential Evolution (DSDE) algorithm significantly improves the global search performance and convergence efficiency of the algorithm by introducing deterministic sequences to enhance population diversity and local search capability. Combining the DR strategy with the improved algorithm provides a new perspective for solving the intermittency and uncertainty problems of RE and is an important addition to the existing research on the economic dispatch of PowSs.

The contribution of the study is to provide a new model that can effectively address the stability and economic challenges in the operation of RES. The model is verified through simulation experiments to show significant results in reducing the peak and valley load differences in the grid, lowering the operating costs, and increasing the utilization of wind power. The test results of the model on multi-modal and fixed dimensional functions show excellent stability and accuracy, demonstrating the effectiveness of the DSDE algorithm in solving complex optimization problems. Furthermore, the implementation results of the model demonstrate that the peak-to-valley load differences, fluctuation amplitude, and operating costs of the system are reduced after considering DR. This not only verifies the practicality of the model but also provides an innovative theoretical foundation and practical guidance for the economic dispatch of the PowS, thereby promoting the development of the RES in the direction of greater efficiency and economy.

2. Methods

2.1 DR model based on real-time elastic electricity price

Due to the randomness, volatility, and intermittency of RE, it is difficult to accurately predict the power supply capacity of RE, thereby increasing the uncertainty and load pressure of power grid operation (Xia *et al*., 2023; Bazionis and Georgilakis, 2021). In response to this, this study proposes a RES-EDM based on DR, which establishes a real-time electricity price DR

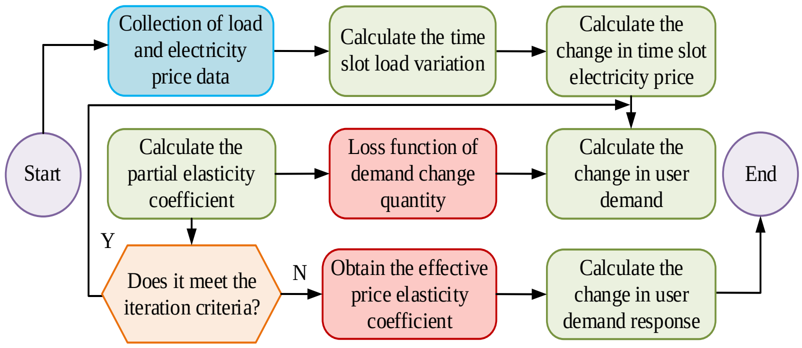


Fig. 1 Demand response model operation process

model through the relationship between electricity quantity and electricity price. This model adopts the charging and discharging strategy of EV, optimizes the flexible load scheduling in the system, and improves the efficiency and reliability of power grid operation. DR, as a market incentive measure, can encourage users to adjust their electricity consumption patterns according to changes in electricity prices, which helps reduce the peak and valley load differences in the power grid and alleviate system scheduling pressure (Ajitha and Sudha, 2023). This paper first constructs a DR model grounded on real-time elastic electricity prices, estimates the elasticity coefficients of electricity prices for different users and time periods through research, creates an elasticity matrix that displays the level of electricity prices, and then designs DR strategies based on this. The DR model operation flowchart is shown in Fig. 1.

In Fig. 1, the model sets start and end dates and collects and analyzes historical load and electricity price data during that period. Then, the model sequentially calculates the changes in load, electricity price, and user demand during the period, quantifying the corresponding changes in electricity load fluctuations, price adjustments, and user demand. The next step is to establish a loss function based on the change amount and evaluate the deviation of demand changes. By optimizing the loss function, the optimal objective function is determined. Subsequently, the gradient descent algorithm is utilized to update the elasticity coefficient of electricity prices and make conditional judgments (Jiabao *et al.*, 2023; Lin *et al.*, 2022). If the iteration condition is met, the demand change step will be repeated until a complete and effective elastic coefficient is obtained. Finally, using the elasticity coefficient of electricity prices, the DR change of users towards electricity price fluctuations is calculated. Among them, the calculation of the electricity price elasticity coefficient is given by equation (1).

$$E_{i,j} = \frac{p_{0,j}}{d_{0,i}} * \frac{\Delta d_i}{\Delta p_j}, j = 1,2,\cdots,24 \quad (1)$$

In equation (1), $p_{0,j}$ and Δp_j are the initial electricity price and electricity price fluctuations at time j. $d_{0,i}$ is the initial power demand of user at time i. Δd_i means the demand change at i. The elasticity matrix can be divided into two types: self-elasticity and cross elasticity. When i and j are the same, users can only adjust their current electricity usage. When i and j are different, users can transfer dispatchable loads to lower cost periods based on electricity price fluctuations, thereby achieving optimized allocation of electricity demand (Zhang *et al.*, 2021; Dong *et al.*, 2022). After implementing the DR strategy, the user's power demand formula is shown in equation (2).

$$q_{ni'} = q_{ni}\left\{1 + \sum_{j=1}^{24} E_{i,j} * \frac{p_i - p_{0,j}}{p_{0,j}}\right\}, i = 1,2,\cdots,24 \quad (2)$$

In equation (2), q_{ni} and $q_{ni'}$ are the initial and adjusted user energy loads. The calculation of the user's DR change is shown in equation (3).

$$\Delta q = \sum_{j=1}^{24} E_{i,j} * \frac{q_{ni}*[p_i(l) - p_{0,j}(l)]}{p_{0,j}(l)}, l = 1,2,\cdots,24 \quad (3)$$

In equation (3), $p_i(l)$ and $p_{0,j}(l)$ are the electricity price and initial electricity price at time i on day l.

2.2 Economic dispatch model for renewable energy systems

After successfully constructing a DR model based on real-time elastic electricity prices, this study combines EV charging and discharging strategies to establish a RES-EDM that

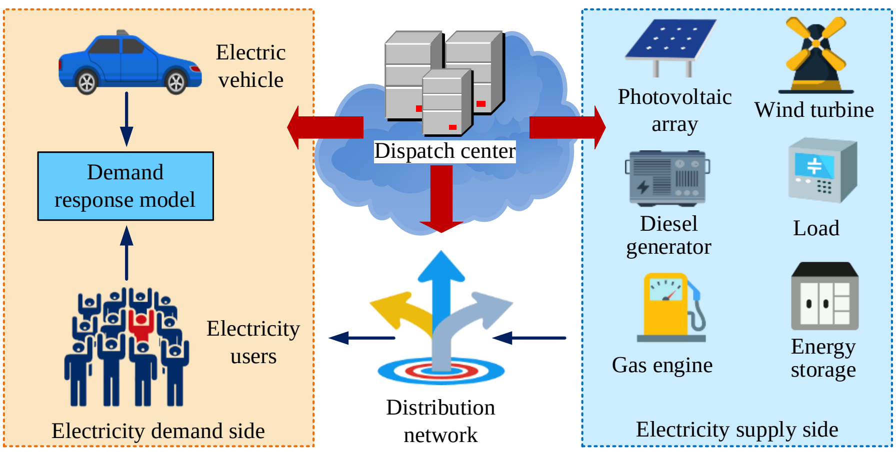


Fig. 2 Economic scheduling model of RES

considers DR. It aims to achieve more efficient and stable energy management. Fig. 2 shows the overall architecture of the model. In Fig. 2, the model mainly consists of four parts: power demand side, power supply side, power grid, and dispatch center. The power supply side is a comprehensive wind power plant that includes multiple wind turbines, as well as auxiliary equipment such as photovoltaic arrays, diesel generators, micro gas turbines, energy storage devices, and loads. It delivers energy to the demand side through integration into the power grid. On the demand side of electricity, the DR model incentivizes users to adjust their energy consumption behavior, allowing them to charge when the grid load is low or electricity prices are cheap while coordinating the charging and discharging behavior of EVs (Serat *et al.*, 2023; Gul and Suchitra, 2024). EVs will store energy during low-demand periods and release energy during peak-demand periods. Furthermore, the model establishes a scheduling center to facilitate the coordination between the power grid, supply side, and demand side. This center is responsible for the real-time scheduling and management of power transmission and consumption.

The model scheduling center is supported and operated by key components such as objective function, constraint conditions, and communication control. These components work together to ensure that the dispatch center effectively manages and optimizes the operation of the PowS (Zhong *et al.*, 2024; Yu *et al.*, 2024). The specific expression of the objective function is given by equation (4).

$$min\ F = min \sum_{t=1}^{T} \sum_{i=1}^{N_G} (a_i P_{Gi,t}^2 + b_i P_{Gi,t} + c_i) \tag{4}$$

In equation (4), F is the total cost of coal consumption. $P_{Gi,t}$ is the actual power of Thermal Power Unit (TPU) i during time period t. a_i is the quadratic cost coefficient. b_i is a cost coefficient. c_i is a fixed cost. T denotes the gross of scheduling periods. N_G is the sum of TPUs. The optimization objective of EDM is to minimize the difference between peak and valley loads after demand side scheduling management. The optimization objective calculation is shown in equation (5).

$$F_L = \min(Load_{\max} - Load_{\min}) \tag{5}$$

In equation (5), $Load_{max}$ is the peak load value, and $Load_{min}$ is the low load value. For the smooth operation of RES, certain conditional constraints are required within EDM (Rajabdorri *et al.*, 2022; Rani and Malakar, 2024). The actual power constraint of the unit is shown in equation (6).

$$\begin{cases} 0 \le P_{W,t} \le P_{W,t}^{\max} \\ P_{Gi,t}^{\min} \le P_{Gi,t} \le P_{Gi,t}^{\max} \end{cases} \tag{6}$$

In equation (6), $P_{W,t}$ and $P_{W,t}^{max}$ are the actual power and expected actual power of the wind turbine during period t. $P_{Gi,t}^{min}$ and $P_{Gi,t}^{max}$ are the minimum and maximum actual power of TPU i during t. The system power balance constraint is shown in equation (7) (Rabiee *et al.*, 2021).

$$g^{it}(\theta^{it}, P^{it}) = 0 \tag{7}$$

In equation (7), g^{it}, θ^{it}, and P^{it} represent the power loss, voltage angle, and actual power of unit i during t. The climbing constraint is shown in equation (8).

$$\begin{cases} 0 \le P_{Gi,t} - P_{Gi,t-1} \le \delta_{i,max+} \\ 0 \le P_{Gi,t-1} - P_{Gi,t} \le \delta_{i,max-} \end{cases} \tag{8}$$

In equation (8), $\delta_{i,max+}$ and $\delta_{i,max-}$ are the Max and Min power increase rates of unit i. The constraint on EV charging and discharging power is shown in equation (9).

$$\begin{cases} P_{ch,t} \le P_{Nch} \\ P_{dis,t} \le P_{Ndis} \end{cases} \tag{9}$$

In equation (9), P_{Nch} and P_{Ndis} are the standard power for charging and discharging the EV group. The constraint on user satisfaction is shown in equation (10).

$$\begin{cases} H_{S,t} \ge H_{S,\min} \\ H_{S,t} = 1 - \dfrac{\left| P_{ev,t} - N_{ev} E_t \right|}{2 P_{Nch}} \end{cases} \tag{10}$$

In equation (10), $H_{S,t}$ and $P_{ev,t}$ are the power service satisfaction and charging/discharging power of the EV group during period t. $H_{S,min}$ denotes the lower limit of satisfaction with electric power services for the EV group. N_{ev} is the number of EV groups. In addition, the YALMIP toolbox is selected as the communication component for the scheduling center, and optimized using the CPLEX solver and DE algorithm (Ding *et al.*, 2023; Arunkumar *et al.*, 2022). The operation flow of RES-EDM is shown in Fig. 3.

In Fig. 3, the first step is to input the power load, elasticity coefficient, and constraint conditions, and solve for the minimum load peak valley difference on the power demand side. After optimizing the load distribution using YALMIP, CPLEX, and DE algorithms, the load curves for EV and DR optimization are generated. The next step is to input the predicted wind power, thermal power parameters, and constraints again, and solve for the minimum cost of TPUs on the power supply side. Similarly, through communication

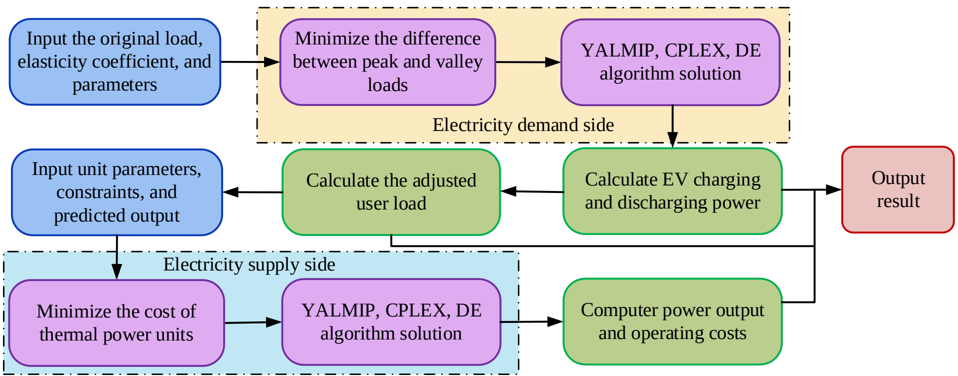


Fig. 3 Demand response model operation process

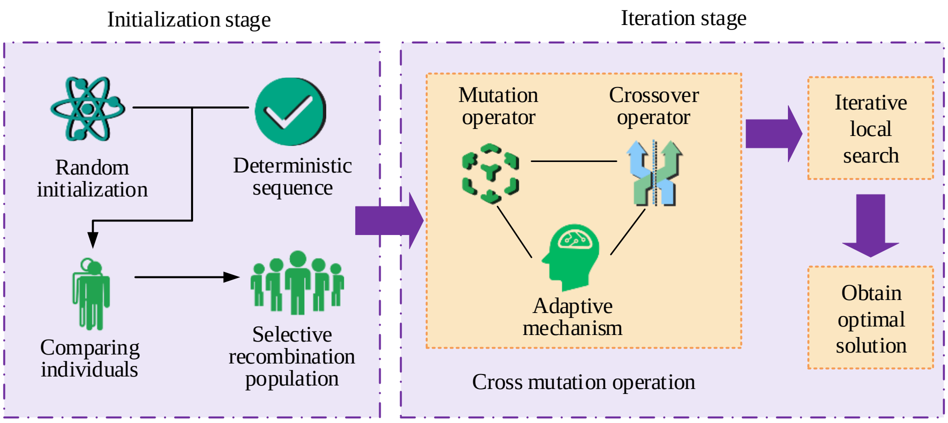


Fig. 4 Overall improvement of DE algorithm

control tools and DE algorithms, the actual power and cost of the units are determined.

2.3 DE algorithm based on deterministic sequence

After a thorough analysis of the construction and objectives of RES-EDM, this study turns to exploring how to effectively solve the complex optimization problems involved in the model. EDM includes multiple factors such as power generation costs, output limitations, and network losses. The DE algorithm excels at handling the complexity of models and can obtain the optimal solution for power generation scheduling based on mutation crossover (Kaihua *et al.*, 2023; Li *et al.*, 2023; Ibrahim *et al.*, 2023). DE is a heuristic random search algorithm proposed by Kenneth Price et al., which solves complex optimization problems by simulating the evolutionary process in nature. It has the advantages of a simple structure, good robustness, and strong global search ability (Ali *et al.*, 2023; Wang *et al.*, 2022). However, due to the influence of greedy selection, this algorithm is prone to getting stuck in local optima. Therefore, this study proposes a DSDE algorithm based on deterministic sequence improvement for the EDM solution of RES. The improvement of the algorithm is shown in Fig. 4.

In Fig. 4, a deterministic sequence is introduced during the population initialization stage to increase the diversity of the population and improve the local search capability of the algorithm. Adding mutation operators and selecting binomial crossover operators in the mutation and crossover operation stages can improve the optimization performance and convergence efficiency of the algorithm. Meanwhile, adaptive strategies can be adopted to dynamically adjust key parameters at each stage, improving the adaptability performance of the algorithm. The DE algorithm adopts a random approach during the population initialization stage, which may result in an uneven distribution of individuals in the search space, leading to poor initial population quality and premature convergence during the iteration process (Chakraborty *et al.*, 2023; Ahmad *et al.*, 2022). To overcome the above drawbacks, this study introduces a deterministic sequence initialization population to ensure that the initial population uniformly covers the key areas of the search space. The population initialization process of the DSDE algorithm is displayed in Fig. 5.

In Fig. 5, Step 1 is to set key parameters such as population size and problem dimension. Step 2 is to determine the boundary of the search space and evenly divide it into several paragraphs. Step 3 is to create and map a deterministic linear increasing sequence, determining each vector segment of the search space. Step 4 is to allocate the population of individuals in an orderly manner to each dimensional space through a mapping function, completing the initialization of individuals. Step 5 is to make conditional judgments on the individual's dimensional values. If the judgment value exceeds the spatial boundary, it is adjusted back to the boundary, otherwise, it is used as the initial population. Among them, the interval expression of the search space is shown in equation (11).

$$I = \frac{x_d^{\max} - x_d^{\min}}{n} \tag{11}$$

In equation (11), I, x_d^{max}, and x_d^{min} are the segment spacing, maximum value, and minimum value of the search space. n is the population size. The segment vector calculation is shown in equation (12).

$$S_k = \begin{cases} x_d^{\min} \ldots k = 1 \\ S_{k-1} + I \ldots k \in [2, n] \\ x_d^{\max} \ldots k = n \end{cases} \tag{12}$$

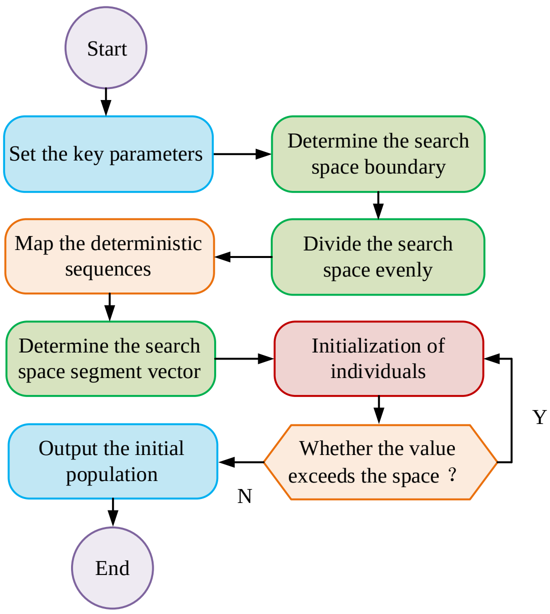


Fig. 5 Population initialization flow for the DSDE algorithm

In equation (12), S_k and I are the vectors and spacing between each segment of the search space. The calculation of individual initial dimension values is given by equation (13).

$$x_{i,d} = x_d^{\min} + S_k * I + rand_{i,d} * I \tag{13}$$

In equation (13), $x_{i,d}$ is the initial dimension value of the individual. $rand_{i,d}$ is a random number generated by individuals and dimensions, with a range of [0,1]. In the DSDE algorithm, crossover mutation is the core part of the algorithm, which works together to generate new candidate solutions for individual populations. During the mutation operation stage, one baseline vector individual and three parent individuals are randomly selected for differential mutation. The calculation of differential vectors is shown in equation (14).

$$v_{r,G} = x_{p1,G} - x_{p2,G} \tag{14}$$

In equation (14), $x_{p1,G}$ is the first parent individual. $x_{p2,G}$ is a second-generation individual. The mutation vector is shown in equation (15).

$$u_{r,G} = x_{t,G} + F * (x_{p3,G} - x_{p2,G}) \tag{15}$$

In equation (15), $x_{t,G}$ is the individual reference vector. $x_{t,d}$ is the scaling factor. $x_{p3,G}$ is a third generation individual. The crossover operation stage is based on the binomial crossover operator to determine dimension inheritance, thereby forming a new offspring population. The population update is shown in equation (16).

$$u_{r,d,G+1} = \begin{cases} u_{r,d,G} \ldots if(rand_d \leq CR, or, j = r) \\ x_{r,d,G} \ldots otherwise \end{cases} \tag{16}$$

In equation (16), is $u_{r,d,G+1}$ the offspring population. $u_{r,d,G}$ and $x_{r,d,G}$ are the dimension value of the mutation vector and current individual. CR is the crossover probability. j is the index that controls cross operations. The high sensitivity of traditional DE algorithms to parameters renders them susceptible to manipulation, thereby affecting the convergence performance of the algorithm. This study introduces an adaptive mechanism that dynamically adjusts the scaling factor and crossover probability based on the algorithm's operational status and resolution quality. After mutation and crossover operations, the DSDE algorithm immediately uses a greedy strategy to determine the optimal solution for the population through conditional judgment. If the offspring individuals are superior to the parent individuals, the offspring individuals are selected as part of the new population. On the contrary, the parent individuals are retained in the new population and iterated until the new population is completely determined.

3. Results

3.1 Experimental setup and dataset

To verify the comprehensive performance of the DSDE-solving algorithm and the feasibility of EDM, this study designs simulation testing experiments. The experimental unified computing environment is the Windows 10 operating system, and the simulation software is MATLAB 2021a. Three benchmark test functions are selected for the experiment to compare the optimization performance of PSO, Bat Algorithm (BA), Butterfly Optimization Algorithm (BOA), and DSDE algorithm. Two RES units with 4 and 5 units are selected as the test objects for the experiment, and the economic optimization scheduling of the system is compared with and without the DR model scenario. The experiment selects the Best Value (BV), Average Value (AV), Stand Deviation (STD), and convergence curve of the function as evaluation indicators for algorithm performance. The actual power of the unit, power Fluctuation Amplitude (FA), Peak Valley Difference (PVD), and Operating Cost (OC) are selected as evaluation indicators for EDM. The experiment fixes all parameters, sets the function to run 100 times, with 30000 EVs, an average vehicle speed of 50km/h, a battery capacity of 40kWh, a charging and discharging efficiency of 0.9, and a lower limit of user satisfaction of 0.5. The rated capacity of the wind farm energy storage unit is 150kWh, the maximum allowable charging and discharging power is 50kWh, the charge capacity range is [30135], and the charge installation cost is 120,000 yuan. Table 1 shows the detailed data of wind farm units.

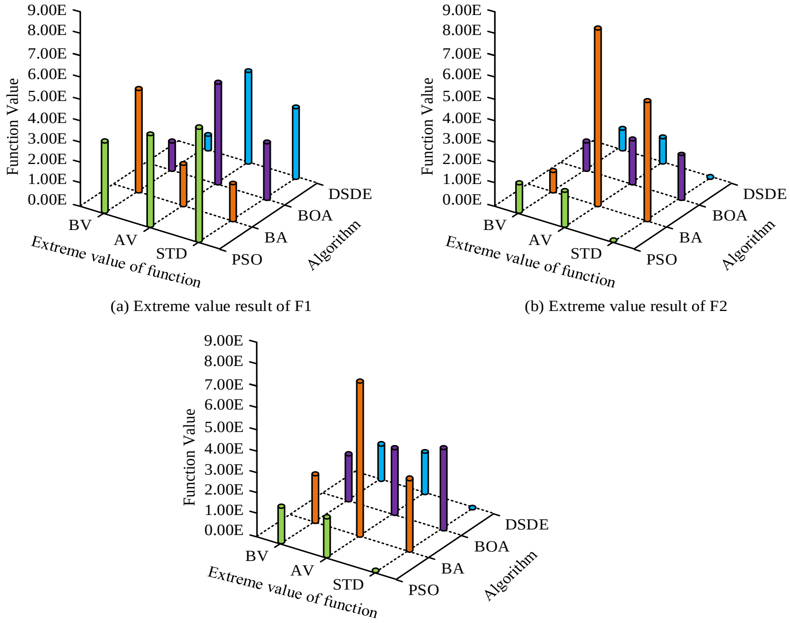
3.2 Performance optimization analysis of solving algorithms

Fig. 6 shows the extreme value test results of various algorithm functions. The DSDE algorithm performs outstandingly in extreme value testing of different types of functions. In the single modal function test, the AV and STD of the DSDE algorithm are the highest, at 6.2560E-08 and 4.3765E-08, indicating a high degree of fluctuation and dispersion in the results. In multimodal function testing, the AV and STD of the DSDE algorithm are significantly lower than other algorithms, at 1.4598E-32 and 0, respectively. Its dataset has extremely high stability and consistency. In the fixed dimensional function test, the AV and STD of the DSDE algorithm are almost lower than other algorithms, at 3.0592E-04 and 0, indicating once again its stability in output results. Overall, although the DSDE algorithm exhibits some volatility on unimodal functions, it demonstrates a high degree of stability and reliability when dealing with multi-modal and fixed-dimensional functions.

Fig. 7 shows a comparison of the convergence curves of the algorithm on the test function. The performance of the DSDE on the test function surpasses that of all other algorithms. In the testing of single modal functions, the curve of the DSDE

Table 1
Specific parameters of the wind farm unit

Wind farm	Set	Maximum effort	Minimum output	a_i	b_i	c_i	Climbing rate
A	1	70	25	0.004	2.50	/	40.50
	2	90	35	0.018	1.75	/	55.00
	3	60	20	0.063	1.50	/	24.50
	4	55	15	0.001	3.25	/	27.50
B	1	500	350	1.011	116.6	5573.1	288.95
	2	100	70	0.063	125.6	1033.7	45.00
	3	130	40	0.045	124.7	5306.5	70.00
	4	100	60	0.063	125.7	1108.6	50.00
	5	450	130	0.015	121.8	4263.1	235.00

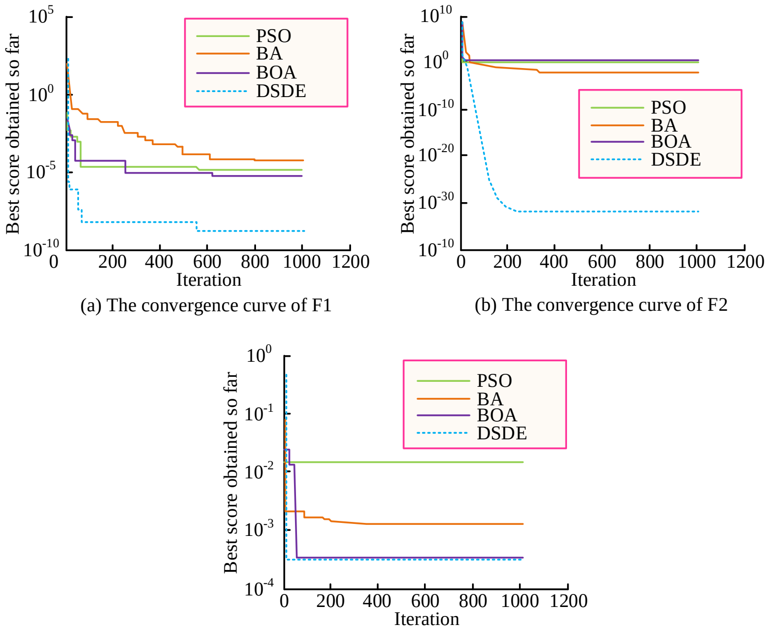


(a) Extreme value result of F1

(b) Extreme value result of F2

(c) Extreme value result of F3

Fig. 6 Bar chart of extreme value test results for algorithm functions



(a) The convergence curve of F1

(b) The convergence curve of F2

(c) The convergence curve of F3

Fig. 7 Convergence curve for solving test functions

shows a deep mining trend, with the fastest convergence speed and highest optimization accuracy. DSDE algorithm converges quickly after 580 iterations, while the convergence speed of the other three algorithms decreases by 3.45%-6.90%. In multi-modal function testing, both the DSDE and BOA algorithms show good convergence, with a clear downward trend in their convergence curves. Among them, the convergence curve of the DSDE is the steepest, with a function BV less than 10^{-30}, showing the highest accuracy, faster convergence rate, and strong stability. In fixed dimensional function testing, all algorithms can quickly find BV and the DSDE has the deepest curve mining depth and the fastest convergence speed, with a function BV below $10^{-3.5}$. Overall, the DSDE outperforms PSO, BA, and BOA in optimization accuracy and convergence speed, and is more effective in avoiding falling into the trap of local optima.

3.3 Analysis of model optimization scheduling results

Fig. 8 shows the optimization results of the RESA model. In Fig. 8 (a), the electrical load of RES fluctuates in a tortuous manner over time. Among them, the load curve FA without considering DR is relatively large, significantly increasing during peak periods and relatively low during low periods. The load curve of DR is more stable, with effective control of load growth

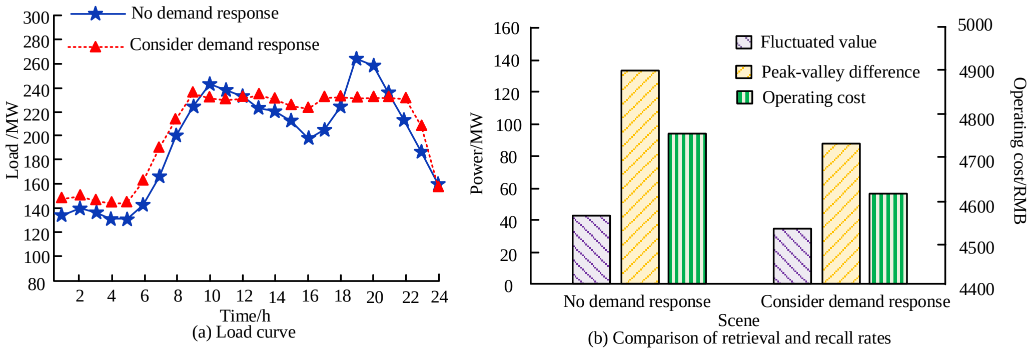


Fig. 8 Model optimization results in the RES-A

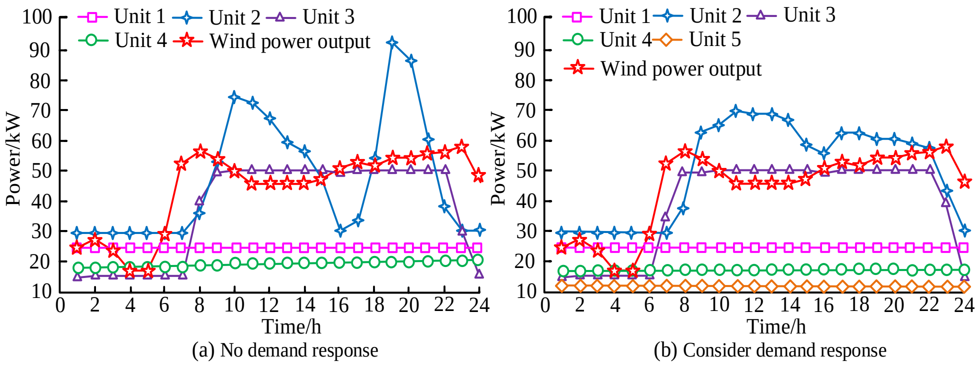


Fig. 9 Output optimization results of units in RES-A

during peak periods and an increase in electricity demand during off-peak periods. In Fig. 8 (b), without considering DR, the system's PVD power consumption reaches 135.15MW, FA is 41.59MW, and OC reaches 47958.55 yuan. After considering DR, the PVD of system power consumption is reduced by 33.30%, and the FA is decreased by 12.07%. The OC is reduced to 46,058.76 yuan, representing a 3.96% cost reduction.

Fig. 9 shows the optimization results of unit output in RES-A. In Fig. 9 (a), without considering DR, the output curves of Unit 2 and Unit 3 show fluctuating changes. The output of Unit 2 fluctuates greatly and is highly unstable, resulting in a limited absorption capacity of the system for wind power generation. In Fig. 9 (b), considering DR, EDM effectively balances the power demand during peak and off-peak periods, reducing the PVD of the system load to 90.15MW. The output curve of Unit 2 is smoother, with a decrease in FA, resulting in a significant improvement in the system's wind power utilization during low load periods.

Fig. 10 shows a comparison of model optimization in RES-B. In Fig. 10 (a), without considering DR, the electricity load curve fluctuates greatly, rising sharply during peak periods and maintaining a low level during low periods. After considering DR, the load curve was well adjusted, with a relatively stable trend during peak electricity consumption periods and a significant increase in load during off-peak periods. In Fig. 10 (b), without considering DR, the system's PVD power consumption is 789.58MW, FA is 245.49MW, and OC reaches 5253.49 yuan. After considering DR, the system's power consumption for PVD, FA, and OC is 527.55MW, 201.79MW, and 52.3315 million yuan.

Fig. 11 shows the optimization results of unit output in RES-B. In Fig. 11 (a), without considering DR, the output curves of Unit 1 and Unit 3 show dynamic changes, playing a positive role in power generation. The output of Unit 3 fluctuates violently, and the system's ability to absorb wind power is poor. In Fig. 11 (b), after considering DR, the system load and grid scheduling achieve effective coordination, promoting interaction between these two sides. The power output of Unit 3 is more stable, while the power output of the newly added Unit 5 remains constant. During periods of low load, the system's ability to absorb wind power is greatly enhanced.

4. Conclusion

The test results of the proposed model on multi-modal function and fixed dimension function show high stability and accuracy, which proves the effectiveness of the DSDE algorithm in solving complex optimization problems. The DSDE algorithm enhances the population diversity and local search ability by introducing deterministic sequences, thereby improving the global search performance and convergence efficiency of the algorithm. This is a novel development in algorithm optimization. The research verifies the actual effect of the model in reducing the peak-valley load difference, reducing the operating cost, and improving the utilization rate of wind power through simulation experiments. The research on effective management of RE through EDM reduces the operating cost and pollution discharge of PowS, which is of great significance in promoting the sustainable development of RE. The research provides an innovative theoretical basis. Combining DR and DE algorithms provides a new perspective for the optimal scheduling of RESs, which is of guiding significance for further research and application in RE in academia and industry.

In response to the problem of poor power supply stability in existing RESs, this study proposed a RES-EDM based on DR strategy and DSDE algorithm. The algorithm performance was evaluated through simulation experiments, and the model

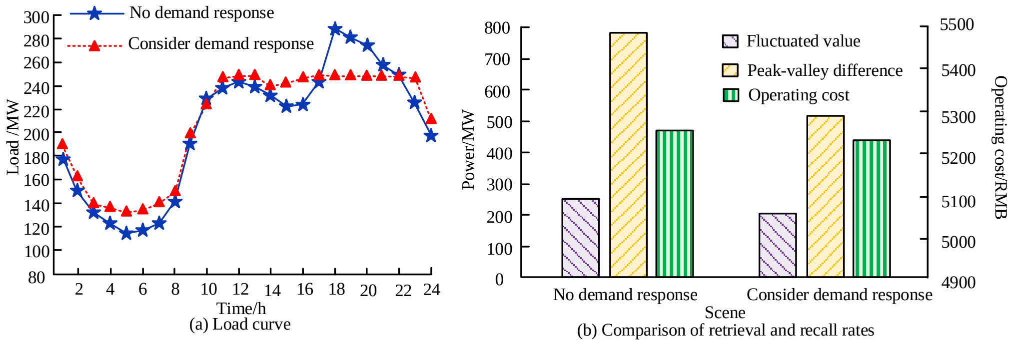


Fig. 10 Model optimization results in the RES-B

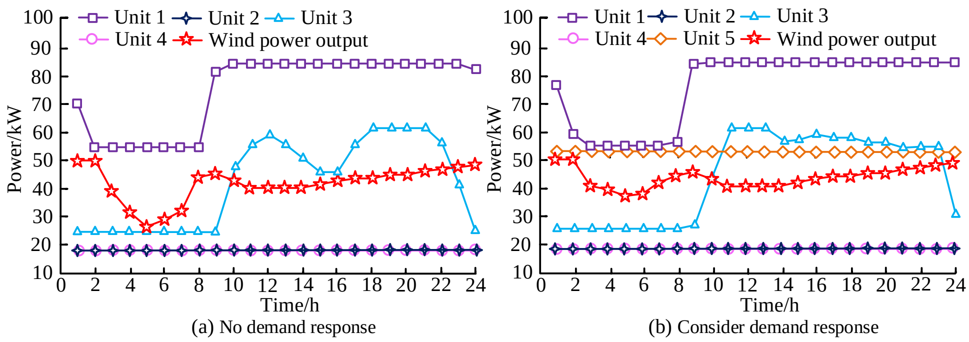


Fig. 11 Output optimization results of units in RES-B

optimization efficiency was analyzed. The experiment showed that in terms of function extremum, the STD of the DSDE algorithm on unimodal functions was 4.3765E-08, and the STD on multi-modal functions and fixed dimensional functions was 0. In terms of the convergence curve, the DSDE algorithm had the highest mining depth and fastest convergence speed, with a multi-modal function BV of less than 10^{-30} and a fixed dimensional function BV of $10^{-3.5}$. After considering DR, the electricity consumption of PVD, FA, and OC for RESA was 90.15MW, 36.57MW, and 46058.76 yuan, while the electricity consumption of PVD, FA, and OC for RESB was 527.55MW, 201.79MW, and 52.3315 million yuan. Research has shown that this model significantly improves the power supply stability and scheduling efficiency of RES, effectively lowering the economic cost.

It is worth mentioning that the proposed EDM has insufficient generalization ability, long solution time, and simple DR measures. In addition, the DR strategy mainly focuses on the charging and discharging behavior of EVs, while the sources of DR in the actual PowS are more diverse. Future research will consider a variety of DR resources, including industrial load, household electricity, etc., aiming to improve the adaptability and robustness of the model. Future research should expand the time scale of DR and the algorithm for solving optimization models, develop multi-layer optimization scheduling strategies and comprehensively improve the overall performance and operational efficiency of RES.

5. Implications

The research results showed that the DR was the key to improving the scheduling efficiency of RES. Policymakers should consider formulating and optimizing DR strategies, such as dynamic electricity price mechanisms and incentive measures, to encourage users to increase consumption during low demand and reduce consumption during peak demand. In addition, to better integrate RE, policy-makers need to consider adjusting the power market structure to allow more flexibility and innovation, such as by introducing energy storage technology and demand-side management tools. EVs have great potential as a DR resource, so it is necessary to promote the integration of EV charging and discharging strategies. Through technological innovation and R&D investment, the modernization of PowS and the widespread application of RE can be supported.

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