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Optimal scheduling strategy based on genetic algorithm for grid-side energy storage system to participate in regional power trading

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Abstract With the increasing global energy demand and environmental problems, energy storage technology is gradually playing an important role in modern power systems. In this study, an optimal scheduling strategy based on genetic algorithm for grid-side energy storage system to participate in regional power trading is proposed. The strategy optimizes the charging and discharging decisions of the energy storage system by genetic algorithm to maximize the revenue. First, an optimization model of the energy storage system is constructed, including power trading, charging and discharging constraints of the energy storage device and the prediction of market electricity price. Then, the multi-objective optimization problem is solved by genetic algorithm to optimize the charging and discharging decisions, and applied to the actual scheduling of grid-side energy storage system. The experimental results show that the energy storage system is able to realize high returns under specific electricity price and load demand conditions. In the specific arithmetic analysis, the improved NSGA-II algorithm is used to optimize the scheduling of the IEEE 33-node power system. The optimized grid-side energy storage system achieves better returns in several time periods, including renewable energy consumption and peak-valley arbitrage in the 14:00-22:00 time period. Under different tariff fluctuation conditions, the energy storage system is able to efficiently dispatch resources, reduce operating costs and enhance market competitiveness. Through further optimization, the scheduling performance of the system is significantly improved and has strong application prospects.

Index Terms Grid-side energy storage system, genetic algorithm, optimal scheduling, revenue maximization, NSGA-II algorithm, electricity market

I. Introduction

With the acceleration of the global energy transition, the share of renewable energy in the power supply has been increasing [1], [2]. Renewable energy sources such as solar energy and wind energy are characterized by intermittency and volatility, which brings challenges to the stable operation of power systems [3]. As a device capable of storing and releasing electric energy, grid-side energy storage system can not only enhance the stability and reliability of the power grid, but also effectively cope with the intermittency and volatility of renewable energy sources and realize the efficient use of energy [4]-[6]. Therefore, the grid-side energy storage system plays an increasingly important role in the regional power market, while the reform of the power market also creates conditions for the energy storage system to participate in regional power trading [7], [8].

Electricity as the cornerstone of modern social operation, its trading mechanism directly affects the efficiency of energy resource allocation [9]. The essence of power trading is to realize the connection between the production, transmission and consumption of electric energy through market-oriented way, which involves the interests of power generation enterprises, power grid companies, the main body of the sale of electricity and end-users and other parties [10]-[12]. After years of reform, China's power market has formed a market system with medium- and long-term trading as the mainstay and spot trading as a supplement, and the trading varieties cover a variety of dimensions, such as electric energy, auxiliary services, renewable energy quotas, etc. [13]-[15]. The traditional power system is mainly composed of power generation, transmission, distribution and sales links, and each link is relatively independent of each other [16]. With the deepening of the power market reform, the power generation side and the power sales side have been gradually liberalized, and the competition mechanism of the regional power market has been gradually established [17], [18]. As a new type of power resource, grid-side energy storage system can participate in market transactions in multiple segments such as power generation, transmission, distribution and sale, injecting new vitality into the development of regional power market [19]-[21].

In this study, the optimal dispatch model of grid-side energy storage system is first constructed. The model mainly considers the participation mode of the energy storage system in the electricity market, and optimizes the charging and discharging decisions of the energy storage devices through the changes of the electricity price forecast and load demand. Specifically, the scheduling problem of the energy storage system is transformed into a multi-objective optimization problem with the objective of maximizing the expected return of the system while satisfying the charging and discharging constraints of the energy storage devices and the constraints of the electricity market. In order to solve this optimization problem, a genetic algorithm is used, and the improved non-dominated sequential genetic algorithm (NSGA-II) is specifically chosen, which is able to obtain better optimization results while ensuring computational efficiency. In the solution process, we first made reasonable assumptions about the relevant parameters of the energy storage system, and designed reasonable power trading rules in combination with the actual grid system. Through the multi-generation optimization of genetic algorithm, we gradually approach the optimal scheduling scheme, and realize the best charging and discharging decision of the energy storage system under different electricity price fluctuations, so as to maximize the revenue. The effectiveness and practicality of the strategy are verified by analyzing the arithmetic case of IEEE 33-node system.

II. Optimal scheduling strategy for grid-side energy storage system

The research object of this section is the grid-side energy storage system that can have an impact on the market, based on the operation mechanism of early bidding in the power market, designing the optimal scheduling strategy for the grid-side energy storage system to participate in the regional power trading, and solving the corresponding optimal scheduling decision by genetic algorithm to achieve the goal of maximizing the expected return.

II. A. Description of parameters

First, this paper initiates a study based on the decision-making of the grid-side energy storage system at discrete time $t \in \{1,2,3,\cdots,T\}$, i.e., the decision-making of power trading in each cycle. Assuming that the maximum storage energy of the grid-side energy storage system is $\bar{E}$, the minimum storage energy is $\underline{E}$, and $\bar{E} > \underline{E} \geq 0$, the storage energy of this energy storage system has a finite value. Assuming that E_t is the amount of electricity in the energy storage system corresponding to moment t, based on discrete time, the vector of electricity that has been stored is $\hat{E} = (E_1, E_2, \cdots, E_T)$ and $E_t \in [\underline{E}, \bar{E}], \forall t \in \{1,2,\cdots,T\}$. For the constraints on the amount of charging and discharging per unit cycle of the energy storage system, it is assumed that the upper and lower limits of charging per unit cycle are $\bar{Q}^p$ and $\underline{Q}^p$, which represent the constraints on the amount of electricity that can be bought from the market by the system per cycle, and that the upper and lower limits of discharging per unit cycle are $\bar{Q}^g$ and $\underline{Q}^g$, i.e., the constraint on the amount of electricity that a firm can sell to the market per cycle. It is assumed that $\underline{Q}^g = \underline{Q}^p = 0$, i.e., the minimum values of charge and discharge per unit cycle are both 0.

Next, consider the efficiency parameters of the energy storage system. For long-term energy storage operation, the loss efficiency is assumed to be $\eta_t \in [0,1]$, which is related to time t. In addition, for the charging and discharging of the energy storage device, the charging efficiency is assumed to be α and the discharging efficiency is assumed to be $\beta, \alpha, \beta \in (0,1]$, so that $1-\alpha$ and $1-\beta$ represent the rate of loss of power for charging and discharging, respectively. In addition, there will be a certain amount of power transmission loss during the transmission of electricity through cables, assuming that the transmission efficiency of the wires is ρ, $\rho \in (0,1]$.

Based on the above assumptions, it can be seen that $\bar{Q}^p / \alpha\rho$ denotes the actual maximum amount of electricity charged to the energy storage device per unit cycle, and $\beta\rho \cdot \bar{Q}^g$ denotes the actual maximum amount of electricity discharged from the energy storage device to the market per unit cycle. Energy storage devices can be categorized into fast-charging systems and slow-charging systems based on their upper and lower charging and discharging limits and the overall amount of energy stored: if $\beta\rho \cdot \bar{Q}^g < \bar{E} - \underline{E}$ or $\bar{Q}^p / \alpha\rho < \bar{E} - \underline{E}$, then the energy storage system is a slow charging system, i.e., the unit cycle does not allow the storage device to be fully charged or fully released. If $\beta\rho \cdot \bar{Q}^g \geq \bar{E} - \underline{E}$ and $\bar{Q}^p / \alpha\rho \geq \bar{E} - \underline{E}$, then the energy storage system is a fast-charging system, i.e., the storage device can be fully charged or fully released per unit cycle. This paper focuses on slow-charging energy storage systems.

In the electricity market, the energy storage system makes power dispatch decisions based on the predicted market electricity price P_t with the goal of revenue maximization. Based on discrete time, the predicted electricity price vector is $P=(P_1,P_2,\cdots,P_T)$. For power scheduling, assume that the power scheduling decisions are $q_i^g(q_i^g>0)$ and $q_i^p(q_t^p>0)$, where q_i^g denotes the amount of power discharged by the firm from the moment of t to the moment of $t+1$, and $q_i^g\cdot\beta\rho$ is the amount of the actual amount of electricity sent to the market; q_i^p denotes the amount of charging by the enterprise from the moment of t to the moment of $t+1$, and $q_i^p/\alpha\rho$ is the actual amount of electricity bought from the market. It is assumed that there is a certain operating cost of the energy storage system in the process of power dispatch, and it is assumed that c denotes the operating cost per unit of power.

In the case of energy arbitrage by power companies, the parameter λ on the intensity of market impact is introduced for the power companies that are price setters, and the linear price function on the intensity of market impact as well as the amount of electricity dispatched is constructed. Based on this, the price after the change is:

$$\hat{P}_t=\begin{cases}P_t+\lambda P_t\dfrac{q_t^p}{\alpha\rho}\\ P_t-\lambda P_t q_t^g\beta\rho\end{cases}\tag{1}$$

In equation (1), the parameter $\lambda\geq 0$ denotes the intensity of the impact of the energy storage enterprise on the market tariff, and if $\lambda=0$, it means that the enterprise has no impact on the market tariff, i.e., it acts as a price taker. $\hat{P}_t$ denotes the market electricity price after the impact.

It is assumed that the two activities of charging and discharging cannot be performed simultaneously, i.e., at any decision moment t, the energy storage system will have three activities: charging, discharging and remaining idle. Therefore, two 0-1 variables U_i^g and U_i^p are assumed to denote the state of charging and discharging of the energy storage system at the moment t, U_i^g denotes the state of discharging, $U_i^g\in\{0,1\}$, and U_i^p denotes the state of charging, $U_i^p\in\{0,1\}$, and $U_i^p+U_i^g\leq 1$, i.e., the energy storage device is in the charging state or the discharging state at any moment, when $U_i^p+U_i^g=1$, or the storage system is in the shutdown state, when $U_t^p+U_t^g=0$.

II. B.Modeling

II. B. 1) Yield function

The expected benefit function obtained at each decision moment of the energy storage system according to its scheduling strategy, the reward function is as follows:

$$R(q_t^p,q_t^g,P_t)=\begin{cases}(P_t-\lambda P_t q_t^g\beta\rho)\cdot q_t^g\cdot\beta\rho-c(q_t^g\cdot\beta\rho)\\ -(P_t+\lambda P_t q_t^p/\alpha\rho)\cdot q_t^p/\alpha\rho-c(q_t^p/\alpha\rho)\end{cases}\tag{2}$$

The first line of equation (2) represents the revenue earned when the energy storage system generates electricity and sells it to the market, based on the firm's tariff forecast, the strength of its market impact, and its operating costs. The second row represents the cost that the energy storage system spends when it buys electricity from the market and deposits it in the energy storage system.

II. B. 2) Constraints

Regarding the state of charging and discharging, according to the universal rule of operation: the two activities of charging and discharging cannot be carried out at the same time, ie:

$$U_t^{\mathrm{p}}+U_t^g\leq 1\tag{3}$$

And according to the physical constraints of the energy storage system, the energy storage system is required to satisfy the upper and lower bound constraints on the charging and discharging of the energy storage system at each decision-making moment, viz:

$$0\leq q_t^g\leq\bar{Q}^g\cdot U_t^g\tag{4}$$

$$0\leq q_t^p\leq\bar{Q}^p\cdot U_t^p\tag{5}$$

At the same time, the charging and discharging amount of the energy storage system at each decision-making moment is also related to the existing power stored in the current energy storage system: when the decision is charging, according to the current existing power and the maximum capacity of the energy storage system, its maximum charging amount can not exceed the difference between the two values, that is:

$$q_t^p \leq \overline{E} - E_t \tag{6}$$

Similarly, when the decision is to discharge, based on the current power available and the minimum capacity of the energy storage system, the maximum discharge should likewise not exceed the difference between the two, viz:

$$q_t^g \leq E_t - \underline{E} \tag{7}$$

The amount of power within the energy storage system will change with the charging and discharging decisions and the efficiency of the process, Eq. (8) represents the stored energy balance or state transition relationship from period t to $t+1$:

$$E_{t+1} = \eta_t (E_t + q_t^p - q_t^g) \tag{8}$$

II. B. 3) Objective and Value Functions

At each decision cycle, i.e., when $t \in \{1,2,3,\cdots,T\}$, the state variables of the energy storage firm are E_i as well as P_i, i.e., $S(t) = S_t(E_t, P_t)$. Given the initial state value S(1), the energy storage firm maximizes its revenue by finding the optimal strategy π^*.

The objective function of the energy storage firm as a price setter is shown below:

$$\max_\pi \sum_{t=1}^{T} E[R(q_t^p, q_t^g, P_t) \mid S(1)] \tag{9}$$

where the state $S(t)$ brought about according to the strategy π adopted at moment t satisfies a random distribution, and therefore the expectation E is introduced. For each decision stage $t \in \{1,2,3,\cdots,T\}$ and the corresponding state $S(t)$, the value function corresponding to each strategy π is as follows:

$$V(S(t)) = R(q_t^p, q_t^g, P_t) + E(V_{t+1}(S(t+1) \mid S(t)) \tag{10}$$

The above equation is equivalent to:

$$V(S(t)) = \max\{V^p(S(t)), V^g(S(t))\} \tag{11}$$

where $V^p(S(t)), V^g(S(t))$ denote the value functions of charging and discharging, respectively, for state $S(t)$ at moment t, viz:

$$V_t^p(S(t)) = -(P_t + \lambda P_t q_t^p / \alpha\rho) \cdot q_t^p / \alpha\rho - c(q_t^p / \alpha\rho) + E[V_{t-4}(S(t+1) \mid S(t)] \tag{12}$$

$$V_t^g(S(t)) = (P_t - \lambda P_t q_t^g \beta\rho) \cdot q_t^g \cdot \beta\rho - c(q_t^g \cdot \beta\rho) + E[V_{t-4}(S(t+1) \mid S(t)] \tag{13}$$

Equation (12) denotes the value function corresponding to the charging decision if it is taken in the case of state $S(t)$ at moment t. Eq. (13) then represents the value function corresponding to taking the charging decision.

III. Model solving based on genetic algorithm

III. A. Multi-objective optimization problem

A multi-objective optimization problem consists of n decision variables, k objective functions to be optimized, m inequality constraints, and p equality constraints:

$$\begin{aligned} &\min/\max\ y = f(x) = (f_1(x), f_2(x), \ldots, f_k(x)), k \geq 2 \\ &s.t.\quad g_i(x) \leq 0, i = 1,2,\ldots,m \\ &h_j(x) = 0, j = 1,2,\ldots,p \end{aligned} \tag{14}$$

Here $x = (x_1, x_2, \ldots, x_n)$ is an n-dimensional decision variable for $x \in R^n$, $f(x)$ is the objective function, $g(x)$ is the m-inequality constraint function, $h_j(x)$ is the p-equality constraint function, and $g_i(x)$ and $h_j(x)$ form the feasible solution region.

III. B. Constraints processing

Intelligent optimization algorithms are stochastic optimization algorithms proposed for unconstrained optimization problems, the existence of constraints must be considered in solving practical optimization problems, constraints lead to the existence of infeasible domains in the search space of the decision variables, and multi-objective optimization with constraints needs to consider both the constraints and the objective function at the same time.

In this paper, the hierarchical penalty function method is used to deal with some of the constraint problems, the expression is given in the following equation:

$$\Phi(x) = f(x) + \sum_{i=1}^{N} \{R_{k,i} \times \max[0, g_i(x)]^2\} \tag{15}$$

where $R_{k,i}$ is the penalty factor for segmentation, which divides the degree of constraint violation into multiple levels, different levels use different penalty factors, and the higher the degree of constraint violation, the larger the value of the penalty factor.

III. C. Data normalization

Data normalization is one of the important steps in the data preprocessing stage, which can make the objective function converge faster. Linear function normalization is to do a linear transformation of the initial data to normalize the range of each value to [0, 1], the normalization formula is as follows:

$$x_0 = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{16}$$

Back-normalize the data according to the following equation:

$$x = (x_{\max} - x_{\min})x^{'} + x_{\min} \tag{17}$$

where x_0 is the normalized value, x is the original value, $x_{\min}$ is the minimum value of the sample data, and $x_{\max}$ is the maximum value of the sample data.

III. D. NSGA-II Algorithm

Multi-objective optimal scheduling of grid-side energy storage systems is essentially a dynamic nonlinear optimization problem with multiple objectives and constraints. In this paper, the improved non-dominated sorting genetic algorithm (NSGA-II) is used for model solving.

(1) Non-dominated sorting method

In NSGA-II, Pareto solution sets are constructed by the non-dominated ordering method. In the population $Pop(t)$ with m individuals in the t th generation, it is assumed that each individual p has two attributes, which are the set S_p consisting of all individuals dominated by an individual p and the number of individuals dominating an individual n_p in the population. First, compute the two attributes of all individuals in the population and put all individuals with $n_p = 0$ into the set F1 and assign their nondominated rank $Rank(p)$ to I. Then, iterate over the individuals q in the set S_p of all individuals in the set F_1, as the individuals p dominating individuals q has been stored in the set F_1, hence $n_q - 1$. If $n_q - 1 = 0$, then individual q is stored in the set F_2 and its nondominated rank is assigned a value of 2. The operation is repeated in a loop until the nondominated ranks of all individuals have been classified.

(2) Crowding degree

Classify all individuals in the population $Pop(t)$ into different non-dominated fronts according to their non-dominated rank. In order to ensure the good diversity of the population, it is necessary to measure the diversity of the population in each non-dominated frontier. NSGA adopts the small habitat technique to maintain the diversity of the population, but the fitness sharing parameter in it is difficult to be determined, for this reason, NSGA-II proposes and uses the degree of crowding to guarantee the diversity of the population. For a two-objective optimization problem, the crowding degree at point i is the sum of the normalized length and width of the solid rectangle in the computed graph. The crowding distance $CD(i)$ of the i th point is denoted as:

$$CD(i)=\frac{|f_1(X_{i+1})-f_1(X_{i-1})|}{\max\limits_{1\le j\le h} f_1(X_j)-\min\limits_{1\le j\le h} f_1(X_j)}+\frac{|f_2(X_{i+1})-f_2(X_{i-1})|}{\max\limits_{1\le j\le h} f_2(X_j)-\min\limits_{1\le j\le h} f_2(X_j)} \tag{18}$$

where h is the number of all individuals in the nondominated frontier where the i th point is located.

In general, for a multi-objective optimization problem with g objectives, the crowding distance $CD(i)$ of the i th point is:

$$CD(i)=\sum_{r=1}^{g}\frac{|f_r(X_{i+1})-f_r(X_{i-1})|}{\max\limits_{1\le j\le h} f_r(X_j)-\min\limits_{1\le j\le h} f_r(X_j)} \tag{19}$$

(3) Elite strategy

After the non-dominated ranking and crowding degree are calculated, individual $i(i=1,2,\cdots,m)$ in population $Pop(t)$ possesses non-dominated rank $Rank(i)$ and crowding degree $CD(i)$. That defines that individual i dominates individual j should satisfy either $Rank(i)<Rank(j)$, or $Rank(i)=Rank(j)$ and $CD(i)>CD(j)$. To ensure that the population after each iteration is better or not worse than the original population, NSGA-II utilizes an elite strategy to select the optimal individuals among the parent and child populations. The parent population P_t and the offspring population Q_t are merged into one set, which is then subjected to non-dominated ordering and crowding ordering, and the top m individuals are selected to form the next generation of the parent population P_{t+1}.

(4) Algorithm flow of NSGA-II

Step 1: Initialize the parent population and then sort the individuals using non-dominated rank and crowding.

Step 2: Based on the parent population, use binary tournament selection, simulated binary crossover and polynomial variation to create the offspring population.

Step 3: Combine the parent and child populations into a single set and evaluate each individual in this set. After going through the non-dominated sorting and crowding calculation, the individuals in the top half of the ranking are selected as the new parent population.

Step 4: Repeat the second and third steps until the stopping condition is satisfied. Finally the Pareto solution set is obtained.

III. E. Improvement of NSGA-II algorithm

The classical NSGA-II algorithm suffers from the disadvantages of insufficient search accuracy and particle uniformity, in order to solve these shortcomings, this paper introduces a Y-NSGA-II algorithm to optimize the strategies of crossover and mutation operators in genetic operations and congestion distance calculation in non-dominated sorting.

(1) Combined crossover operator

The NSGA-II algorithm is encoded using simulated binary crossover operator (SBX), which selects x_1 and x_2 parent individuals and generates child individuals c_1 and c_2 according to the following equation:

$$\begin{cases} c_{1,i}=\dfrac{(1+\beta)x_{1,i}}{2}+\dfrac{(1-\beta)x_{2,i}}{2} \\ c_{2,i}=\dfrac{(1-\beta)x_{1,i}}{2}+\dfrac{(1+\beta)x_{2,i}}{2} \end{cases} \tag{20}$$

where $x_{1,i}$ and $x_{2,i}$ are the i th generation of parent individuals x_1 and x_2, and $c_{1,i}$ and $c_{2,i}$ are the i th generation of offspring individuals c_1 and c_2, respectively.

The β is a uniformly distributed factor calculated as follows:

$$\beta=\begin{cases} (2\gamma)^{\frac{1}{\mu+1}}, \gamma\le 0.5 \\ \left[\dfrac{1}{2(1-\gamma)}\right]^{\frac{1}{\mu+1}}, \gamma>0.5 \end{cases} \tag{21}$$

where γ is a (0, 1) uniform random number and μ is the cross-distribution index.

The SBX operator has a small search space and poor global search capability. To address the shortcomings of the SBX operator, a combinatorial crossover operator NDX is introduced to improve the algorithm's global search ability and convergence speed, and the positive-too distribution is introduced into the simulated binary crossover operator, with the uniform distribution factor β replaced by 1. 481*N, and N is a positive-too distributed positive random variable with the following formula:

$$\begin{cases} c_{1,i} = \dfrac{x_{1,i} + x_{2,i}}{2} + 1.481N\dfrac{x_{1,i} - x_{2,i}}{2} \\ c_{2,i} = \dfrac{x_{1,i} + x_{2,i}}{2} - 1.481N\dfrac{x_{1,i} - x_{2,i}}{2} \end{cases} \tag{22}$$

At the beginning of the algorithm iteration, more NDX crossover operators are used to increase the search range and improve the global optimization ability. In the late iteration of the algorithm, the solution set converges to the Pareto optimal solution, and more SBX crossover operators are used to improve the local search ability and accelerate the convergence speed.

(2) Combined variation operator

The variation operator in NSGA-II algorithm often uses polynomial variation, in order to obtain better performance in the variation optimization process, this paper uses a new type of combined variation operator, which is able to select the most effective variation in different iteration cycles. The specific method is as follows:

$$u_{k+1} = \begin{cases} u_k + U(-\sigma_1, \sigma_2) & t \le T/4 \\ u_k + C(0, \sigma_2) & T/4 < t \le 3T/4 \\ u_k + N(0, \sigma_3) & 3T/4 < t \le T \end{cases} \tag{23}$$

Uniform variation is the replacement of the original gene value on the individual code with a random number that conforms to a range of uniform distributions is appropriate at the beginning of the algorithm. Gaussian variation refers to replacing the original gene values with a random number that is positively distributed with restricted mean and variance. Cauchy variation refers to the use of the Cauchy distribution to generate random numbers away from the zero point to improve the global search capability.

Combined variance operator is a combination of uniform variance operator, Gaussian variance operator and Cauchy variance operator, which is used in the early stage of the algorithm iteration to obtain strong global search ability, in the middle stage of the algorithm iteration to use Cauchy variance operator, which has moderate global and local search ability, and in the late stage of the algorithm iteration to use Gaussian variance operator.

(3) Dynamic congestion strategy

In order to solve the defects in practical applications, this paper introduces a dynamic crowding degree strategy. After recording the individual with the largest crowding degree, the individual is eliminated and the crowding degree of the remaining individuals in the layer is recalculated and sorted, then the individual with the largest crowding degree is recorded and eliminated in the new sorting, the crowding degree of the remaining individuals is updated, and the above process of recording, elimination, and sorting is repeated until the number of recorded individuals meets the requirements and stops.

III. F. Algorithm testing

III. F. 1) Test Functions

In order to test the convergence accuracy and running speed of the improved Y-NSGA-II algorithm in real optimization problems, this paper selects three representative objective functions: Sphere, Rosenbrock and Griewank, which are classical nonlinear test functions, namely, single-peak, no-peak, and multiple-peak functions. By comparing the optimization results of different optimization algorithms on the above three objective functions in multiple dimensions, the optimization ability of Y-NSGA-II algorithm is verified.

In this paper, the adaptive inertia weight particle swarm algorithm, which is currently popular in the field of optimization algorithms, and the traditional non-dominated sorting genetic algorithm (NSGA-II) are selected as the control algorithms for experiments, and the optimization search calculations are carried out by the three algorithms on the above three objective benchmark functions.

III. F. 2) Test results

Optimization calculations are carried out on the three dimensions of the benchmark objective function, and the specific iteration results of the three benchmark objective functions are shown in Figures 1 to 3. After a number of comparison tests, this paper will run the optimal results of each algorithm in different dimensions and different benchmark objective functions for statistics, the statistical results of various algorithms in the benchmark objective function are shown in Table 1. Compared with the traditional non-dominated sorting genetic algorithm, the optimal solution obtained by the improved non-dominated sorting genetic algorithm is closer to the optimal solution in the three dimensions of the three benchmark objective functions after performing the same number of generations of optimization operations, which effectively improves the optimization-seeking ability of the NSGA-II algorithm. Its effect is especially obvious on the Griewank function, which is a multi-peak function. The optimal values of the objective function of the Y-NSGA-II algorithm on the three test functions are 2.43184E-8, 5.57964E-10 and 0.47858, respectively.

Comparing the experimental data of the traditional NSGA-II algorithm and the adaptive inertia weight particle swarm algorithm, it can be found that after the optimization operation of the same number of generations, the optimization ability of the particle swarm algorithm is much larger than that of the traditional NSGA-II algorithm, but in the running time of the algorithm, the running time of the NSGA-II algorithm is much smaller than that of the particle swarm algorithm, so it can be inferred that the NSGA-II algorithm has a more fast optimization ability.

Comparing the experimental data of Y-NSGA-II algorithm and particle swarm algorithm, it can be found that the optimization ability of Y-NSGA-II algorithm is much higher than that of particle swarm algorithm in Sphere function and Rosenbrock function after the optimization operation with the same number of generations, especially in the single-peak function, the accuracy of the optimal solution of Y-NSGA-II algorithm is tens of times higher than that of particle swarm algorithm. Y-NSGA-II is tens of times more accurate than the particle swarm algorithm in finding optimal solutions. In the Griewank function, the optimization ability of Y-NSGA-II algorithm is slightly lower than that of the particle swarm algorithm in the same number of generations, but the difference is not much, which is of the same order of magnitude, and the average values of the objective function are 0.65535 and 0.93449, respectively, and the computation time of Y-NSGA-II algorithm is much lower than that of the particle swarm algorithm, and the Y-NSGA-II algorithm can be used in more iterations. Y-NSGA-II algorithm can achieve the same optimization ability as the particle swarm algorithm through more iterations and parameter adjustments.

Table 1: Statistical results of various algorithms in different benchmark objective functions

		Sphere	Rosenbrock	Griewank
PSO	Optimum value	0.01942	7.84868E-7	0.20450
	Mean value	0.34944	2.16391E-4	0.65535
NSGA-II	Optimum value	0.38444	2.21033E-5	2.83803
	Mean value	0.53608	0.02116	16.33094
Y-NSGA-II	Optimum value	2.43184E-8	5.57964E-10	0.47858
	Mean value	0.04196	4.00102E-6	0.93449

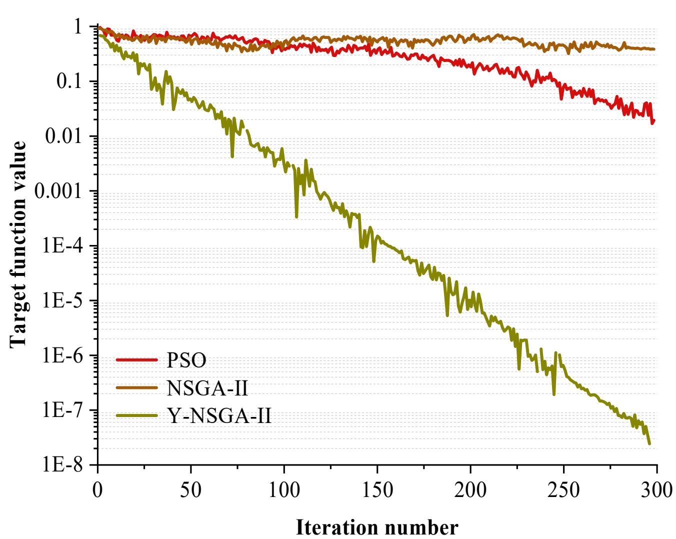

Figure 1: Convergence of algorithm in Sphere function

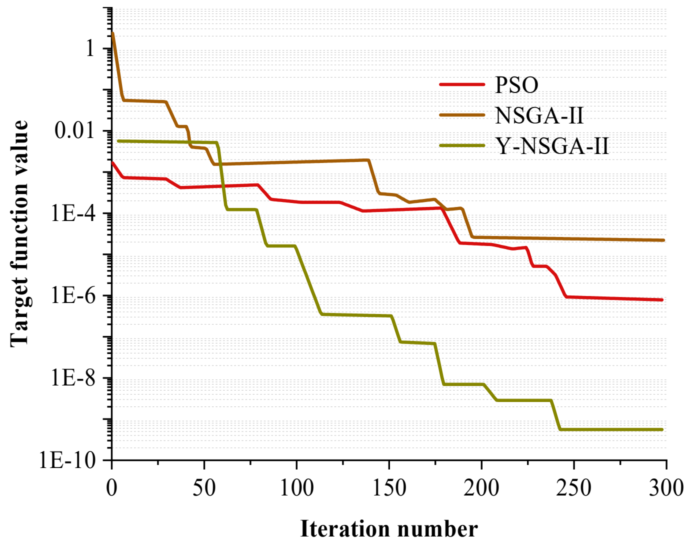

Figure 2: Algorithm converges in Rosenbrock function

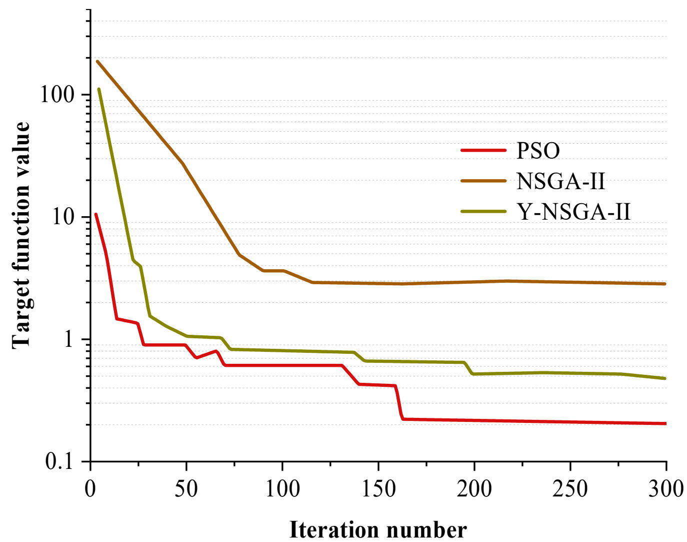

Figure 3: Convergence of the algorithm in Griewank function

IV. Example analysis

IV. A. System parameters

In this section, the improved IEEE 33-node system is taken as an example for simulation and analysis. The base power of the system is set to be 10 MV-Á, the rated voltage is 12.66 kV, and the allowable voltage fluctuation of the system ranges from 0.95 p.u. to 1.05 p.u., and the dollar exchange rate is converted. The grid includes wind turbines (WT), photovoltaics (PV), micro gas turbines (MT), and energy storage systems (ESS).

The Y-NSGA-II algorithm is used to solve the problem in the MÁTLÁB R2022a compilation environment with the Simulink multi-intelligence body simulation framework. The grid-side energy storage system scheduling model is built on the MÁTLÁB/Simulink platform. Set the model to stop training when the average reward is 100 or higher for 200 consecutive times.

IV. B. Scheduling results and analysis

In this section, we carry out an example analysis of the grid-side energy storage system dispatch power trading model, and collect information on renewable energy output, load information, and power purchase and sale tariffs of the grid-side energy storage system in a typical day as model inputs. Based on the power information reported by the grid, the system determines the internal purchase and sale tariffs for inter-grid transactions by combining the grid time-sharing tariffs and feed-in tariffs, and feeds this tariff information back to the grid system, prompting it to dispatch internal resources. The grid-side energy storage system continuously adjusts its action strategy according to the power and price information obtained from the other side, until it converges to the maximum gain. At this time, the internal purchase and sale of electricity and the time-sharing and feed-in tariff curves for each time period are shown in Figure 4.

It can be seen that in 08:00-10:00, 15:00-18:00 and 21:00-24:00 time periods, the electricity sale price is the same as the grid time-sharing price, when the grid power difference is higher and the net load demand is larger, so the price can be increased appropriately to obtain higher revenue. During the 14:00-22:00 time period, the internal power purchase price is generally higher than the feed-in tariff, and the renewable energy output is more abundant, so the grid is encouraged to prioritize the consumption of renewable energy in the region and adjust the dispatchable resources to sell power to operators. During the periods 00:00-06:00 and 23:00-24:00, renewable energy output is generally lower, and the grid system prioritizes internal resource dispatch to meet loads in the region.

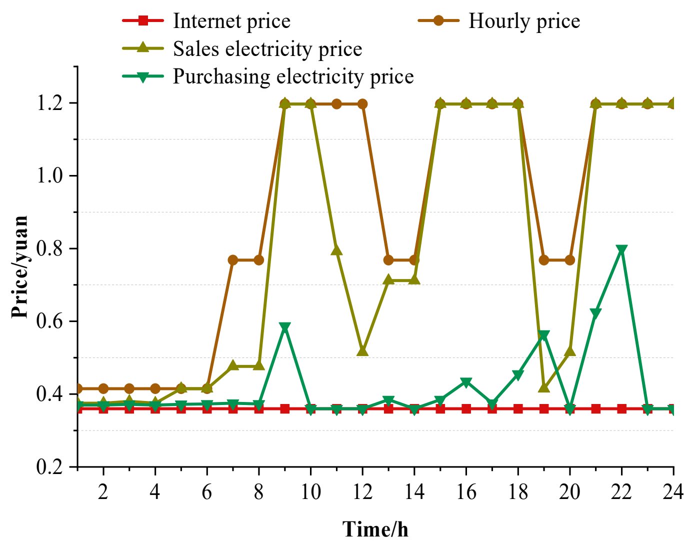

Figure 4: Curves of purchasing and selling electricity price

Fig. 5 illustrates the arithmetic dispatch results. It can be seen that when the trading price is high, the grid prioritizes the consumption of renewable energy and at the same time tends to turn on the micro-gas turbine MT to produce more power to meet the load demand with relatively low operating cost. During off-peak hours, the energy storage system stores energy at a lower price and discharges it when the price is higher, realizing “peak and valley arbitrage”. During 01:00-08:00, the system's renewable energy output meets the load demand, so the energy is sold. At high selling prices, the grid tends to produce more power through storage systems or micro-gas turbine MTs, but when load demand exceeds the grid's supply capacity, the grid must purchase power from operators. Overall, grid-side energy storage systems flexibly manage dispatchable resources in the area, respond to external information, and stabilize supply demand.

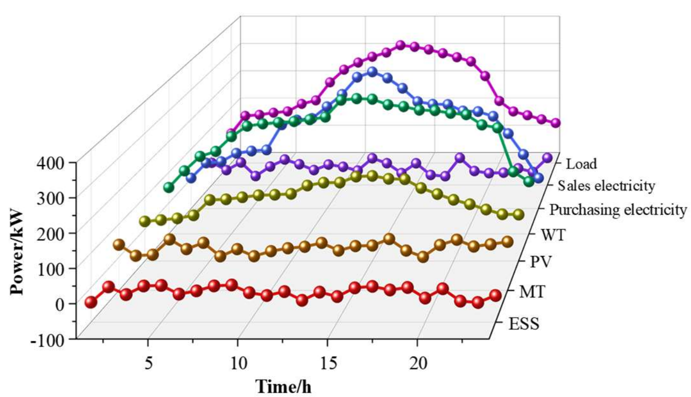

Figure 5: Scheduling results of the example

V. Conclusion

The optimal scheduling strategy for grid-side energy storage system based on genetic algorithm proposed in this study maximizes the revenue by optimizing the charging and discharging decisions of the energy storage system. In the case study, the scheduling results of the system show that the energy storage system can effectively utilize the fluctuation of the market price of electricity to carry out “peak and valley arbitrage” in different time periods, which improves the economic efficiency of the system. The experimental results show that in the 14:00-22:00 period, the renewable energy output is more sufficient, the energy storage system can prioritize the consumption of renewable energy, and through the adjustment of dispatchable resources to the operator to sell electricity. During high tariff hours, the energy storage system obtains higher revenue by discharging electricity. During low tariff periods, the storage system stores more power by charging to provide reserves for later discharges.

In addition, the optimized energy storage system maintains higher revenues during multiple time periods and reduces operating costs through proper power dispatch. By comparing with the traditional method, the improved NSGA-II algorithm shows better performance in terms of solution accuracy and computational efficiency. The study shows that the scheduling strategy is of great practical significance in the practical application of grid-side energy storage systems, and provides an effective tool for power companies to obtain higher revenues in the power market.

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