Research on Optimization Matching of Wind/Solar/Hydro/Storage Flexibility Resource System Considering Electric Vehicle Access

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Research on Optimization Matching of Wind/ Solar/ Hydro/ Storage Flexibility Resource System Considering Electric Vehicle Access

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Abstract. With the development of distributed generation technology and the requirement of power system flexibility, the research on multiple flexible resource optimization is carried out. Based on the traditional optimal configuration of wind-solar-hydro-storage system, this paper takes electric vehicle into consideration. Firstly, the model of each flexible resource is established. Then, a comprehensive evaluation index system is built. Taking the flexible resources in a city on the eastern coast of China as a case, multi-objective grey wolf optimization algorithm and entropy weight method are applied to do the optimization and evaluation. The simulation result shows that in the optimal configuration, not only the renewable resources can be effectively utilized, but also the requirement of load in different period can be meet. Moreover, the total investment can be greatly reduced. In addition, the participation of electric vehicles can not only improve the performance of the hybrid system, but also increase the income of EV holders.

1. Introduction

With the continuous development and maturity of distributed power technology, microgrid and electric vehicle V2G technology, more and more flexible resources are connected to the power grid, which improves the flexibility of the power system [1]. At the same time, the optimal allocation of multi-scale multi-scale flexible resources and the comprehensive evaluation method of matching degree need to be solved. Flexibility resources are widely distributed in various parts of the power system "source-network-load-storage" [2]. The narrowly defined flexible resources refer to distributed power sources on the distribution network side, such as wind turbines, photovoltaics, small hydropower, etc. Electric vehicles and energy storage devices. This article is only for the narrow sense of flexibility resources.

For multi-flexible resource generation systems, most of the existing research focuses on power modeling, optimization simulation and evaluation of two- or three-dimensional flexible resources such as wind/light, wind/water or wind/light/storage [3-5], for the access of electric vehicles, only the matching with a single distributed power source is considered [6-11] and less consideration includes wind turbines, photovoltaic power plants, hydroelectric generators, energy storage and electric vehicles. Matching schemes and optimization strategies for comprehensive flexible resources.

In this paper, a mathematical model is established for the output and charging and discharging of wind water storage and electric vehicles. Then the objective function, constraints and optimization algorithms of the multi-objective optimization problem are determined, and the synthesis is based on the optimization solution set. Preferred strategy. Based on the above theory, combined with the actual examples in a certain area of eastern China, the optimization simulation research is carried out, and the charging and discharging situation of electric vehicles in one day is analyzed in detail.

2. Scenery water storage model

2.1. Wind turbine output model

The relationship between the output power of the fan and the wind speed at the hub height of the fan can be fitted using a polynomial. This paper uses the following cubic function model to calculate:

$$P_{WT}(v)=\begin{cases} 0 & v<v_{ci},\ \ v\geq v_{co} \\ P_N\dfrac{v^3-v_{ci}^3}{v_N^3-v_{ci}^3} & v_{ci}\leq v<v_N \\ P_N & v_N\leq v<v_{co} \end{cases} \tag{1}$$

In the middle , $P_{WT}(v)$ is the maximum output power when the wind speed is v at the hub height, P_N is the rated power of the fan, v is converted into the wind speed at the height of the fan hub, v_N is the rated wind speed, v_{in} is the cut-in wind speed, and v_{out} is the cut-out wind speed.

2.2. Photovoltaic power generation model

The steady-state power output of the PV module uses the following simplified model [9] (under standard test conditions, the solar radiation intensity is 1000 W/m^2 and the battery temperature is 25 °C).

$$P_{PV}=P_{STC}\frac{G_{ING}}{G_{STC}}\left[1+k(T_c-T_r)\right] \tag{2}$$

Where P_{PV} is the actual output power (*kW*)of the PV module; G_{STC} is the solar radiation intensity (*W/m²*)under standard test conditions; P_{STC} is the maximum output power (*kW*) of the PV module under standard test conditions; k is the temperature coefficient of power (%/°C). Where T_c is the temperature of the photovoltaic cell; T_a is the ambient temperature; T_r is the reference temperature; G_{ING} is the actual solar radiation intensity (W/m^2).

On the basis of considering the output of the photovoltaic array, the output of the photovoltaic power generation system needs to comprehensively consider the factors of converter efficiency, maximum power tracking control efficiency and surface area of the photovoltaic array, which affect the efficiency of the power generation system. The average output power of a photovoltaic power generation system over a certain period of time is:

$$PV_{avipower}=\eta_{loss}\eta_{mppt}\eta_{dust}P_{PV} \tag{3}$$

Where η_{loss} is the DC/DC converter efficiency, η_{mppt} is the maximum power tracking control efficiency, and η_{dust} is the power output derating factor of the photovoltaic power generation system due to surface area dust.

2.3. Small hydropower generation power model

Hydroelectric power is a way of generating electricity that converts the potential and kinetic energy of water into mechanical energy and then converts mechanical energy into electrical energy. Water conservancy projects concentrate the drop of natural water flow, forming a water head, so that the water in the upstream reservoir has a higher potential energy, and the energy is converted into electric energy by the turbine.

The turbine head H refers to the total unit flow difference of the turbine inlet and outlet sections. The basic expression is as follows:

$$H=\left(Z_1+\frac{p_1}{\rho g}+\frac{\alpha_1 v_1^2}{2g}\right)-\left(Z_2+\frac{p_2}{\rho g}+\frac{\alpha_2 v_2^2}{2g}\right) \tag{4}$$

Where Z is the unit potential energy relative to the reference plane; ρ is the density of water; $\frac{p_1}{\rho g}$, $\frac{p_2}{\rho g}$ is the unit pressure energy; v_1,v_2 is the average flow velocity of the cross section; $\frac{v_1^2}{2g}$, $\frac{v_2^2}{2g}$ is the unit kinetic energy; α_1 and α_2 are the distribution along the section considering the flow velocity Uneven kinetic energy unevenness coefficient.

The rated output of the turbine is as shown in equation (5):

$$P_{\mathrm{HD}}=9.81\eta Q_d\left(H_d-\Delta H\right) \tag{5}$$

Where H_d is the design head, ΔH is the head loss, Q_d is the design flow, and η is the turbine efficiency. P_{HD} is the power output by the turbine.

2.4. Energy storage and discharge model

The energy of the battery in a hybrid system is constantly changing. At the time t, the charge of the battery is related to the charge at the previous moment and the supply and demand of the charge at time t-1 to time t. When the total output power of renewable energy generation is greater than the load power consumption, the battery is in a charging state, and vice versa, the battery is in a discharging state.

When the battery is charged, $P_{BAT}(t)<0$, the charge at the t hour is

$$SOC(t)=SOC(t-1)-P_{BAT}(t)\eta_C-D_BQ_B^S \tag{6}$$

When the battery is discharged, $P_{BAT}(t)>0$, the charge at the t hour is

$$SOC(t)=SOC(t-1)-P_{BAT}(t)/\eta_D-D_BQ_B^S \tag{7}$$

Where $SOC(t)$ is the remaining capacity of the battery at the tth hour; $P_{BAT}(t)$ is the charge and discharge power of the battery at the tth hour; η_C and η_D are the charge and discharge efficiencies of the battery; D_B is the self-discharge ratio of the battery per hour; Q_B^S is the total capacity of the battery .

2.5. Electric vehicle scheduling model

As a kind of mobile energy storage, electric vehicles have received extensive attention and research in recent years [12-14].

The charge of the electric vehicle at time t is related to the charge at the previous moment and the charge and discharge during this period. When the electric vehicle is in a charging state, its charge at time t is:

$$EV(\mathrm{t})=EV(t-1)+\frac{t_{charge}}{\tau_{EV}}E_{\max} \tag{8}$$

Where $EV(\mathrm{t})$ and $EV(\mathrm{t}\text{-}1)$ are the charge amounts of the electric vehicle at time t and time t-1, respectively; t_{charge} is the charging time; τ_{EV} is the time required for the electric vehicle to fully charge; $E_{\max}$ is the upper limit of the charging amount of the electric vehicle.

When the electric vehicle is in a discharged state, its charge at time t can be expressed as:

$$EV(t)=EV(t-1)-\frac{t_{discharge}}{\eta_{conv}}P_{discharge} \tag{9}$$

Where $t_{discharge}$ is the discharge time, $P_{discharge}$ is the discharge power, and η_{conv} is the inverter efficiency.

The scheduling of electric vehicles needs to consider economics, that is, the charge and discharge price of each time period. The charging and discharging prices of electric vehicles are shown in Table 1 [12].

Table 1. Electric Vehicle Charging and Discharging Price

Time slot	Charging price /RMB	Discharge price /RMB	Time slot	Charging price /RMB	Discharge price /RMB
0:00-1:00	0.320	0.335	1:00-2:00	0.320	0.335
2:00-3:00	0.320	0.335	3:00-4:00	0.320	0.335
4:00-5:00	0.320	0.335	5:00-6:00	0.320	0.335
6:00-7:00	0.320	0.335	7:00-8:00	0.670	0.781
8:00-9:00	0.670	0.781	9:00-10:00	0.670	0.781
10:00-11:00	0.910	1.253	11:00-12:00	0.910	1.253
12:00-13:00	0.910	1.253	13:00-14:00	0.910	1.253
14:00-15:00	0.910	1.253	15:00-16:00	0.670	0.781
16:00-17:00	0.670	0.781	17:00-18:00	0.670	0.781
18:00-19:00	0.910	1.253	19:00-20:00	0.910	1.253
20:00-21:00	0.910	1.253	21:00-22:00	0.670	0.781
22:00-23:00	0.670	0.781	23:00-24:00	0.320	0.335

3. Multi-objective optimization matching model

3.1. Multi-objective optimization overview

The essential difference between multi-objective and single-objective optimization problems is that the solution is not unique and is a set of multiple Pareto optimal solutions. Compared to single-objective optimization, multi-objective optimization can consider the requirements of various indicators.

Multi-objective optimization problems can be summarized as follows:

$$\begin{aligned} &\min F(\mathbf{X}) = \min\left(f_1(\mathbf{X}), f_2(\mathbf{X}), \cdots, f_n(\mathbf{X})\right) \\ &s.t. \quad \mathbf{X} \in \mathbf{\Omega} \\ &\mathbf{G}(\mathbf{X}) = 0 \\ &\mathbf{H}(\mathbf{X}) \le 0 \end{aligned} \tag{10}$$

Where ***X*** is the optimization variable; f_i is the ith optimization goal; $\mathbf{\Omega}$ is the feasible solution space; ***G*** and ***H*** represent the set of equality constraints and inequality constraints, respectively.

3.2. Objective function

(1)The lowest total combined cost

$$\min \quad f_1 = \sum_{i=1}^{N} N_i \cdot (C_i + M_i) \tag{11}$$

Where N, C_i and M_i are the discounted values of wind turbines, photovoltaic power generation systems, hydroelectric energy storage systems, and electric vehicle charging piles, equipment investment construction costs, and maintenance costs, respectively.

(2)The lowest probability of loss of load

$$\min \quad f_2 = \sum_{t=1}^{T} \left(-S_{LOLP}(t) \cdot W(t)\right) / \sum_{t=1}^{T} Q_L(t) \tag{12}$$

Where $W(t)$ is the amount of energy imbalance at a certain moment; $S_{LOLP}(t)$ is a Boolean quantity, when $W(t) \ge 0$, $S_{LOLP}(t) = 0$,when $W(t) < 0$, $S_{LOLP}(t) = 1$; $Q_L(t)$ is the current demand load demand; T is the simulation duration.

(3)Clean energy waste rate is the lowest

$$\min \quad f_3 = \sum_{t=1}^{T}\left(S_{LOEP}(t)\cdot\left(W(t)-Q_B\right)\right) / \left(\gamma\cdot\sum_{t=1}^{T}Q_L(t)\right) \tag{13}$$

Where $W(t)$ is the amount of energy imbalance at a certain time; Q_B is the available capacity of energy storage; γ is the charging efficiency of energy storage; $S_{LOEP}(t)$ is the Boolean quantity, then $W(t)\leq \mathrm{Q_B}$, $S_{LOEP}(t)=0$, then $W(t)>Q_B$, $S_{LOEP}(t)=1$; $Q_L(t)$ is the current time load demand ; T is the simulation duration.

3.3. Restrictions

(1)System active power balance

$$P_{WT}(t)+P_{PV}(t)+P_{HD}(t)+P_{BAT}(t)+P_{EV}(t)=Q_L(t) \tag{14}$$

Where $P_{WT}(t)$, $P_{PV}(t)$, $P_{HD}(t)$, $P_{BAT}(t)$, $P_{EV}(t)$ are the actual powers of the wind turbine, photovoltaic cell, energy storage system and electric vehicle at the simulation time t, $P_{BAT}(t)$ is positive for energy storage discharge, and $P_{BAT}(t)$ is negative for energy storage. Charging, $P_{EV}(t)$ is positive for electric vehicle discharge, and $P_{EV}(t)$ negative for electric vehicle charging. $Q_L(t)$ is the load demand at the moment.

(2)Flexibility resource generation constraint

$$\begin{cases} 0\leq P_{WT}(t)\leq P_{WT}^{\max} \\ 0\leq P_{PV}(t)\leq P_{PV}^{\max} \\ 0\leq P_{HD}(t)\leq P_{HD}^{\max} \\ P_{BAT}^{\min}\leq P_{BAT}(t)\leq P_{BAT}^{\max} \\ P_{EV}^{\min}\leq P_{EV}(t)\leq P_{EV}^{\max} \end{cases} \tag{15}$$

Where $P_{WT}^{\max}$, $P_{PV}^{\max}$, $P_{HD}^{\max}$ are the upper limit of the output of wind turbines, photovoltaic cells and hydroelectric generators, respectively, $P_{BAT}^{\min}$ and $P_{BAT}^{\max}$ are the upper and lower limits of the charge and discharge of energy storage, respectively, $P_{EV}^{\min}$ and $P_{EV}^{\max}$ are respectively charge and discharge of electric vehicles. The upper and lower limits.

(3)Battery charge constraint

$$\begin{cases} SOC^{\min}\leq SOC(t)\leq SOC^{\max} \\ EV^{\min}\leq EV(t)\leq EV^{\max} \end{cases} \tag{16}$$

In the formula, $SOC^{\min}$ and $SOC^{\max}$ are the upper and lower limits of the stored energy, and $EV^{\min}$ and $EV^{\max}$ are the upper and lower limits of the electric vehicle battery.

3.4. Multi-objective optimization algorithm

Grey Wolf Optimization (GWO) is an optimization algorithm proposed by scientists such as Seyedali Mirjalili in recent years [15-16]. The basic idea of the algorithm is the optimization algorithm based on the grey wolf population mechanism and predation behavior. The basic steps for its optimal solution are as follows [17]:

(1)Distribution of population levels

The wolves follow a strict hierarchy, in which the individual with the best fitness value is α wolf, followed by β wolf and δ wolf, and the rest are ω wolves. In the GWO algorithm, the hunting

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behavior is led by α wolf, β wolf and δ wolf, and ω wolf is responsible for following the three wolves to find the optimal solution.

(2)Surrounded by prey

The gray wolf determines the distance between himself and the prey when he surrounds the prey:

$$D = \left| C \cdot X_p(t) - X(t) \right|$$
$$C = 2r_1 \tag{17}$$

Where $X_p(t)$ is the prey position, $X(t)$ is the gray wolf position, and C is the rocking coefficient. r_1 is a random number between 0 and 1.

Then, the gray wolf updates its position based on the distance between itself and the prey:

$$X(t+1) = X_p(t) - A \cdot D$$
$$A = 2ar_2 - a \tag{18}$$

(3)Capture prey

In the gray wolf algorithm, the gray wolf does not know the specific position of the prey. In order to capture the prey, the position information of α wolf, β wolf and δ wolf is used to realize the positioning of the prey. Its mathematical expression is as follows:

$$D_\alpha = \left| C_1 \cdot X_\alpha(t) - X(t) \right|, X_1 = X_\alpha - A_1 \cdot D_\alpha \tag{19}$$

$$D_\beta = \left| C_2 \cdot X_\beta(t) - X(t) \right|, X_2 = X_\beta - A_2 \cdot D_\beta \tag{20}$$

$$D_\delta = \left| C_1 \cdot X_\delta(t) - X(t) \right|, X_3 = X_\delta - A_3 \cdot D_\delta \tag{21}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{22}$$

The multi-target grey wolf algorithm adds Pareto archiving mechanism and α wolf, β wolf and δ wolf selection mechanism based on the grey wolf algorithm. A new solution is generated in each cycle of the algorithm. The Pareto solution is used to store the Pareto solution in these new solutions. The size of the archive is N. When the number of solutions stored in Pareto exceeds N, the congestion distance is used. Make a cut. The nearest solution to each individual i is the domain of i, and α wolf, β wolf, and δ wolf are selected according to the non-dominant relationship. If the solutions do not dominate each other, then the selection is based on the crowded distance.

3.5. Multi-objective optimization algorithm

The entropy weight method [16] is an objective weighting method. The entropy value of each index can indicate the amount of information they provide. Therefore, the weight of each indicator can be determined according to the entropy value. The entropy weight method gives weight by the entropy value of the indicator, which can highlight the local difference of the data. In the evaluation, for a certain indicator, if the sample has a larger difference in this indicator, then the role of this indicator in the evaluation of the program is greater. Otherwise, the samples are the same, and this indicator plays a small role in the evaluation of the program. The calculation steps are as follows:

(1)Data standardization:

The data samples of each indicator are standardized. Suppose that K indicators $X_1,\ X_2, \cdots X_K$, where $X_i = \{x_{i1}, x_{i2}, \cdots x_{in}\}$, that is, each data contains n samples, the formula for normalizing the data is as follows:

$$Y_{ij} = \frac{x_{ij} - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{23}$$

Where Y_{ij} represents the value of the data j normalized by the i index.

(2)Information Entropy of Indicators

Calculate Information Entropy of Indicators. According to the definition of information entropy [18-20], a set of formulas for calculating j information entropy of data are as follows:

$$E_j = -\ln(n)^{-1} \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{24}$$

Where $p_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}}$ and $\lim_{p_{ij} \to 0} p_{ij} \ln p_{ij} = 0$.

(3)Find the information entropy of each indicator:

According to the calculation formula of information entropy, it can be concluded that the information entropy of each index is $E_1, E_2, \ldots, E_k$, and the calculation formula for calculating the weight of each index by information entropy is as follows:

$$\omega_i = \frac{1 - E_i}{k - \sum E_i} (i = 1,2,\ldots,k) \tag{25}$$

Where ω_i is the weight of the indicator i, and k is a total of k indicators.

According to this principle, the comprehensive evaluation index CEI for the multi-objective planning problem can be obtained:

$$CEI = \omega_1 \cdot \bar{f}_1 + \omega_2 \cdot \bar{f}_2 + \omega_3 \cdot \bar{f}_3 \tag{26}$$

Where $\omega_1, \omega_2, \omega_3$ are the weighting coefficients calculated according to the entropy weight method, satisfying $\omega_1 + \omega_2 + \omega_3 = 1$; $\bar{f}_1$, $\bar{f}_2$, $\bar{f}_3$ are the normalized values of the objective functions.

Finally, according to the comprehensive evaluation index value CEI of each pre-selection scheme, the ranking is based on small to large, and the scheme with the highest ranking is the power supply configuration proposal.

4. Study analysis

4.1. Simulation background

This paper selects the average value of wind, light, water and load for a three-year period in a certain area on the eastern coast of China as a typical year.

(1)The typical annual wind, light, water resources distribution and load curve are shown in Figure 1.

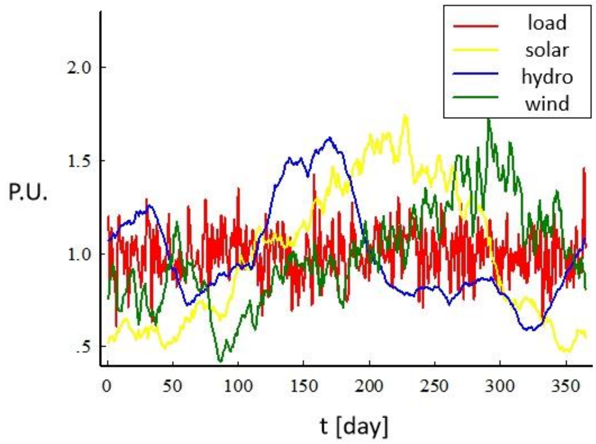

Figure 1. Wind-Solar-Hydro-Load Curves of a City on the Eastern Coast of China in a Typical Year

(2)The parameters of each flexible resource in the hybrid system are shown in Appendix A1-A4.

(3)There are a total of 50 electric vehicles that can be dispatched in the region. The upper limit of charging power is 15kW per hour, and the upper limit of discharge power is 30kW, which is $P_{EV}^{\min} = -15kW$, $P_{EV}^{\max} = 30kW$.

4.2. Simulation background

In this paper, the MOGWO algorithm is used to solve the above multi-objective optimization problem. The wolf size is set to 100, the archive size is set to 50, the number of iterations is set to 50, and the field size is set to 8.

The Pareto solution set is obtained through simulation optimization. The weight coefficients f_1, f_2, f_3 of the objective functions $\omega_1 = 0.7$, $\omega_2 = 0.1$, $\omega_3 = 0.2$,are obtained according to the entropy weight method described in equation (25), and normalized by the equation (23) , and the equation (26) is obtained. (24) Calculate the comprehensive evaluation indicators of each program. The candidate schemes are sorted in ascending order according to the comprehensive evaluation index, and Table 2 is the scheme of the top 10 in the ranking.

Table 2 Results of Ranking based on CEI

Plan number	Fan model	Quantity	Photo voltaic model	Quantity	Energy storage model	Quantity	Turbine model	Quantity	LOEP /%	LOLP /%	NPC/RMB
1	2	1	3	12	1	9	1	2	109.4	0.0000	281457
2	2	1	2	9	1	9	1	2	109.4	0.0000	282040
3	2	1	3	15	1	9	1	2	109.4	0.0000	283311
4	2	1	3	18	1	9	1	2	109.4	0.0000	285165
5	2	1	3	12	1	6	1	2	109.7	0.0637	254906
6	2	1	2	9	1	6	1	2	109.7	0.0637	255490
7	2	1	3	15	1	6	1	2	109.7	0.0637	256760
8	2	1	3	18	1	6	1	2	109.7	0.0637	258614
9	1	2	3	12	1	6	1	1	38.3	0.1719	262545
10	1	2	2	9	1	6	1	1	38.3	0.1719	263128

Considering the various index factors comprehensively, finally, the first-ranking scheme in Table 2 is selected, and each flexible resource is optimally configured, which is the optimal configuration scheme.

LOEP and LOLP are selected as optimization targets respectively, and MOPSO and MOGWO algorithms are used to optimize the solution respectively. The Pareto fronts are shown in Figure 2. It can be seen from the figure that the Pareto frontier obtained by MOGWO is closer to the real situation, and its distribution is more uniform. Therefore, the MOGWO algorithm is used to solve the optimal configuration problem, which has certain advantages compared with other algorithms.

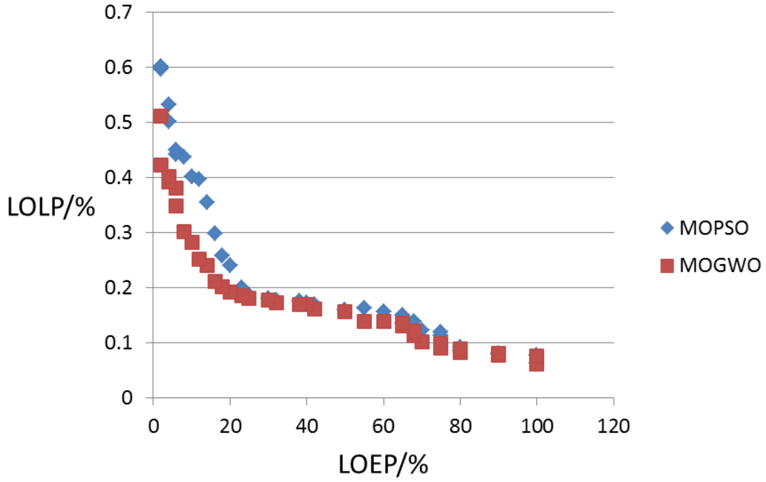

Figure 2. Pareto Fronts Comparison Using Different Optimization Algorithms

Change the ratio of the amount of power generated by the flexible resource to the amount of load γ . The proportion of the energy storage configuration corresponding to the power generation component of different flexible resources is shown in Fig. 3.

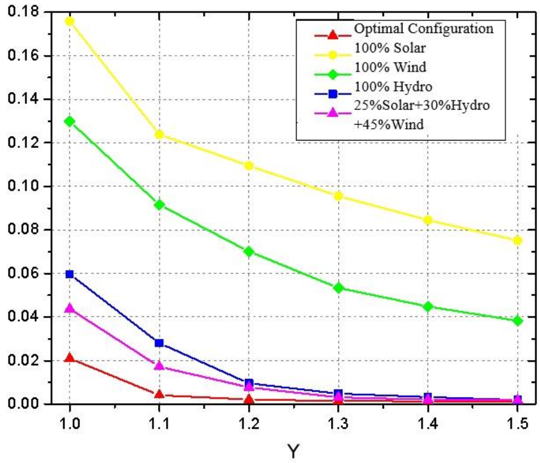

Figure 3. Wind-Solar-Hydro-Load Curves of a City on the Eastern Coast of China in a Typical Year

As can be seen from Fig. 3, the energy storage capacity of the required configuration decreases as the new energy generation increases than γ . According to the analysis, the allocation of more new energy power generation equipment will reduce the capacity of the energy storage device, and also increase the power generation cost of the new energy configuration. At the same time, it will make abandon the new energy that is often stored and cannot be stored, thus causing waste. At the same new energy generation ratio, a significant reduction in energy storage configuration capacity can be achieved by optimizing various new energy allocation ratios. The new energy source such as wind, light, and small hydropower is used as a new energy power generation equipment to meet the power supply reliability, and the required energy storage capacity is relatively large. This not only increases the allocation cost of energy storage capacity, but also increases the investment cost of new energy power generation equipment and wastes of generating new energy. It can be seen that the optimized configuration scheme obtained in this paper will be able to achieve the optimization of the new energy generation ratio and minimize the capacity ratio of the energy storage device.

For the optimal configuration scheme, the operating conditions of one of the days are randomly selected, and the 24-hour charging and discharging of the electric vehicle is as follows:

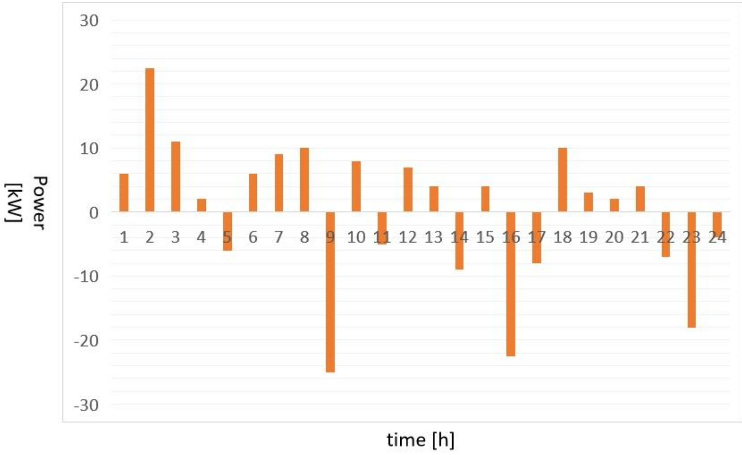

Figure 4. Daily Charging and Discharging Diagram of Electric Vehicles in Optimal Configuration

It can be seen from Fig. 4 that the discharge time period of the electric vehicle is mainly distributed in three time periods of 9:00-10:00, 16:00-17:00 and 22:00-24:00. The charging and discharging situation of electric vehicles is mainly affected by the charging and discharging price of electric vehicles, the load of the grid and the output of other micro-power sources in the hybrid energy system. In general, the load during the day is higher at 9:00-11:00, 14:00-17:00, and 20:00-22:00. Referring to Table 1, the discharge price of the electric vehicle V2G is higher during the above period. In addition, due to the lack of illumination at night, the photovoltaic output is almost zero, so the electric vehicle has a large discharge at 22:00-24:00. In the period from 0:00 to 7:00, the electric vehicle charging power is large because the grid load is not high and the electric vehicle charging price is low. In summary, electric vehicles as a flexible mobile energy storage access have unique advantages for reducing energy storage pressure, grid peaking and valley filling, and increasing vehicle owners' income.

5. Conclusion

Based on the detailed analysis of each flexible resource, this paper establishes a multi-objective optimization model for wind/solar/water/storage/vehicle multi-flexibility resource system, and solves and optimizes it. This model makes up for the incomplete problem of traditional hybrid energy optimization considerations. After comparative analysis, the optimized configuration scheme can achieve the optimization of new energy generation ratio and minimize the capacity ratio of the energy storage device. In addition, the access of electric vehicles has significant advantages in improving the performance of multi-flexible resource systems, making up for the insufficiency of traditional energy storage and reducing the economic investment of the system.

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References

[1] XIAO Dingyao, WANG Chengmin, ZENG Pingliang, et al. Flexibility Resource Optimization Dispatch Considering Short-Term Flexibility Demand and Invoking Cost[J]. Automation of Electric Power Systems, 2014, 42(5):0809-0815.
[2] XIAO Dingyao. Research on Evaluation and Optimization of Power System Flexibility with Large Scales of Renewable Energies[D]. Shanghai Jiaotong University for the Degree of Master, 2015,1.

[3] XIA Yonghong, WU Hongjian, XIN Jianbo, et al. Evaluation of economic operation for microgrid with complementary DGs and energy storage[J]. Electric Power Automation Equipment, 2017, 37(7): 63–69.
[4] MONFORTI F, HULD T, BODIS K, et al. Assessing complementarity of wind and solar resources for energy production in Italy: a Monte Carlo approach[J]. Renewable Energy, 2014, 63(1): 576-586.
[5] YE Lin, QU Xiaoxu, YAO Yanxiang, et al. Analysis on Intraday Operation Characteristics of Hybrid Wind-solar-hydro Power Generation System[J]. Automation of Electric Power Systems, 2018,42(4):158-164.
[6] SUN Bo, DONG Hao, FAN Yanan, et al. Optimal Dispatch Algorithm of Electric Vehicle Interconnected with Distributed PV Under Different Circumstances[J]. Electric Power Construction,2017,38(10):99-107.
[7] WANG Jing, WANG Lili, GUO Yong, et al. Microgrid Economic Dispatch Method Considering Electric Vehicles[J]. Power System Protection and Control, 2016, 44(17):111-117.
[8] MAO Meiqin, SUN Shujuan, SU Jianhui, Economic Analysis of a Microgrid with Wind/Photovoltaic/Storages and Electric Vehicles[J]. Automation of Electric Power Systems, 2011.35(14):30-35.
[9] TAN Lijuan, ZHAO Caihong, CHEN Ziqi, et al. Economical Dispatch for Microgrids of Electric Vehicles and Distributed Power[J]. Power System and Clean Energy,2015.31(4):100-105.
[10] WEI Dajun, ZHANG Chenghui, SUN Bo, et al. A Time-of-Use Price Based Multi-Objective Optimal Dispatching for Charging and Discharging of Electric Vehicles[J]. Power System Technology,2014.38(11):2972-2977.
[11] Gavanidou E,Bakirtzis A G． Design of a stand alone system with renewable energy sources using trade off methods[J]． IEEE Trans. on Energy Conversion,1992,7(1):42-48．
[12] LIU C, Chau K T, WU D, et al. Opportunities and Challenges of Vehicle-to-Home, Vehicle-to-Vehicle and Vehicle-to-Grid Technologies[J]. Proceedings of the IEEE,2013,101(11):2409-2427.
[13] Niklas R, Marija I. Optimal Charge Control of Plug-in Hybrid Electric Vehicles in Deregulated Electricity Markets[J]. IEEE Transactions on Power System, 2011, 26(3):1021-1029.
[14] WU Xinhua, ZHAO Xingyong, JIA Yanbing, et al. Capacity Allocation of Grid-connected Microgrid Optimized in Consideration of Electric Motorcar[J]. Electrical Automation, 2018,40(1):36-39.
[15] LI Xing, YANG Xiuyuan, WANG Lijie. Grey Wolf Algorithm in Coordinated Hydro and Wind Power Generation[J]. Power Generation Technology, 2018,39(1):43-48.
[16] NIU Jiabin, WANG Hui. A Hybrid Strategy-based Grey Wolf Optimization Algorithm. Journal of Qiqihar University(Natural Science Edition),2018,34(1):16-19,32.
[17] MAO Senmao, QU Kaiping, CHEN Yixuan, et al. Grey Wolf Multi-objective Optimizer for Optimal Carbon-energy Combined-flow. The Journal of New Industrialization,2016,6(9):11-17.
[18] JIA Zhengyuan, ZHAO Liang. Comprehensive Evaluation of Power Quality based on the Model of Entropy Weight and Unascertained Measure[J]. Power System Protection and Control,2010,38(15):33-37．
[19] OUYANG Sen, SHI Yili. A New Improved Entropy Method and Its Application in Power Quality Evaluation[J]. Automation of Electric Power Systems, 2013,37(21):156-164.
[20] WANG Jiandong. Research on Fuzzy Comprehensive Risk Evaluation for PV Power Enterprises Based on AHP-Entropy Weight Method[D]. Harbin Institute of Technology for the Degree of Doctor, 2017.6.