Multi-objective Optimal Scheduling for Improving Renewable Energy Consumption Considering Energy Storage Participation

Jiehui Cheng1*, Huiyuan Zhang1, Jun Xu1, Ziqi Wang1
1 Electrical engineering, North China Electric Power University, Beijing 102206, China
Jiehui Cheng to whom any correspondence should be addressed.
*1182201324@ncepu.edu.cn
* Corresponding author’s e-mail: huijiu19965@foxmail.com

Abstract. In response to global environmental crisis and energy exhaustion, the renewable energy resources represented by solar and wind energy have been rapidly developed. In order to make full use of the dispatch resources within the regional power grid, the multi-objective optimal scheduling for improving renewable energy consumption considering energy storage participation is studied. Firstly, the charging and discharging state of the multi-point arrangement of energy storage device are judged according to the source and load status of regional power grid. Secondly, considering the operation constraints of the actual system, taking the total operation cost and network loss of regional power grid as the objective functions, the improved multi-objective search algorithm based on particle swarm optimization algorithm is used to solve the model. Finally, the actual power grid in Xinjiang of China is used as an example for simulation calculations. The simulation results show that the proposed multi-objective optimal scheduling method can significantly improve the system economy, suppress the fluctuation of the upper-level exchange power, and at the same time take into account the renewable energy consumption capacity, which is conducive to the safe and stable operation of the regional power grid.

1. Introduction
Recently, scholars have found that an energy storage system (ESS) can be configured, which can control the fluctuation of the output of renewable energy to make it have a certain degree of controllability, thereby improving the acceptance level of renewable energy in the regional power grid [1-3]. In [4], researchers have proposed an adaptive optimal control strategy for energy storage systems based on an adaptive dynamic programming method. In [5], energy storage optimization control method based on chance constraint programming was proposed to achieve the goal of increasing wind power utilization efficiency. In [6], in order to reduce the adverse effects of large-scale renewable energy grid-connected power systems, a hydropower-photovoltaic-wind energy hybrid power generation system scheduling model was proposed.

Considering the multi-point arrangement of energy storage devices which have the advantages of "plug and play" and wide geographical distribution [7-8], and in order to improve the renewable energy consumption, this paper proposes a multi-objective optimal scheduling for improving renewable energy consumption considering energy storage participation. Firstly, the charging and discharging state of energy storage device are judged. Secondly, considering the operation constraints of the actual system,
the improved multi-objective search algorithm based on particle swarm optimization algorithm is used to solve the model. Finally, the simulation results show the effectiveness and superiority of the proposed method.

2. Optimal scheduling method for energy storage participation to improve renewable energy consumption

Calculate the difference between the sum of the load and the output of the power generation unit based on the predicted output of wind power, photovoltaic, conventional thermal power unit, and load, and record it as d1.

If d1 is greater than 0, the system load demand is large and the output of the power generation unit cannot meet the load demand. At this time, the status of each energy storage unit is queried. If d1 is within the operating constraints of the energy storage unit, the battery discharge meets the load shortage power, and at the same time, the optimized multi-objective search algorithm based on particle swarm optimization optimizes the discharge power of each energy storage unit; If d1 exceeds the operating constraints of the energy storage unit, it will purchase electricity from the higher-level power grid, and at the same time optimize the discharge capacity of the energy storage unit and the upper-level exchange power plan through an improved multi-objective search algorithm based on particle swarm optimization.

Correspondingly, if d1 is less than 0, the system load demand is small, and the output of the power generation unit exceeds the load demand. At this time, query the status of each energy storage unit. If d1 is within the operating constraints of the energy storage unit, the battery charge meets the load shortage power, and at the same time, the optimized multi-objective search algorithm based on particle swarm optimization optimizes the discharge power of each energy storage unit; If d1 exceeds the energy storage unit operating constraints, it sells electricity to the higher-level power grid, and at the same time optimizes the energy storage unit charging capacity and upper-level exchange power plan through an improved multi-objective search algorithm based on particle swarm optimization.

3. Multi-objective optimization scheduling model

3.1. objective function

In order to ensure the minimum total operation cost and network loss of regional power gird, the objective function is established as

\[ F_1 = \min \sum_{i=1}^{T} \left( C_{bat}(t) + C_{line1}(t) \right) \] (1)

\[ F_2 = \min \sum_{i=1}^{T} \sum_{j=1}^{a} R_{j,t} \frac{P_{j,t}^2 + Q_{j,t}^2}{V_{j,t}^2} \] (2)

\[ C_{bat}(t) = \sum_{i=1}^{n_{bat}} \left( C_{bat1,t} - C_{bat2,t} \right) \] (3)

\[ C_{bat1,t} = c_{bat1,t} \left( P_{dis,i,t} - P_{ch,i,t} \right) \] (4)

\[ C_{bat2,t} = \left( P_{dis,i,t} + P_{ch,i,t} \right) c_{price,t} \] (5)

\[ C_{line1,t} = c_{price,t} P_{line,t} \] (6)

where \( C_{bat}(t) \) is the Energy storage unit operating cost function, \( C_{line1}(t) \) is the operation cost of superior tie line, \( T \) is the total number of time slots for optimal scheduling, \( a \) is the total number of branches of regional power grid, \( R_{j,t}, P_{j,t}, Q_{j,t}, V_{j,t} \) are the resistance, active power, reactive power and terminal voltage amplitude of branch j at time t respectively, \( C_{bat1,t}, C_{bat2,t} \) are the operating cost of
the energy storage unit and the operating power income respectively, \( n_{\text{bat}} \) is the total number of energy storage units, \( c_{\text{bat},i,t} \), \( P_{\text{dis},i,t} \), \( P_{\text{ch},i,t} \) are the unit operating cost, charging power and discharging power of the energy storage unit \( i \) at time \( t \) respectively, \( c_{\text{price},t} \) is the regional grid peak and valley electricity prices, and \( P_{\text{line},t} \) is the higher-level exchange power.

3.2. Constraint conditions

3.2.1. The power balance constraint

\[
P_{\text{line}} = \sum_{m=1}^{M} P_{\text{load},m} - \sum_{j=1}^{n_{\text{WT}}} P_{\text{WT},j} - \sum_{k=1}^{n_{\text{PV}}} P_{\text{PV},k} + \sum_{i=1}^{n_{\text{bat}}} P_{\text{bat},i}
\]  

(7)

where \( P_{\text{load},m} \) is the load power at node \( m \), \( P_{\text{WT},j} \), \( P_{\text{PV},k} \), \( P_{\text{bat},i} \) are the output power of wind turbine \( j \)-, photovoltaic unit \( k \), and energy storage unit \( i \) respectively, and \( n_{\text{WT}} \), \( n_{\text{PV}} \) are the number of wind power and photovoltaic units respectively.

3.2.2. Energy storage unit constraints

1) Energy storage unit state constraints

\[
\begin{align*}
SOC_i & = SOC_{i-1} (1 - \delta) + \eta_c \frac{P_{\text{ch},i} \Delta t}{E_{\text{ESS}}} X_i \\
SOC_i & = SOC_{i-1} (1 - \delta) + \frac{P_{\text{dis},i} \Delta t}{\eta_d E_{\text{ESS}}} Y_i
\end{align*}
\]

(8)

where \( SOC_i \), \( SOC_{i-1} \) are the state of charge of the energy storage unit at time \( t \) and time \( t-1 \) respectively, \( \delta \) is the self-discharge rate, \( \eta_c \), \( \eta_d \) are the charge and discharge efficiency of the energy storage unit respectively, \( \Delta t \) is the time interval, \( E_{\text{ESS}} \) is the rated capacity of energy storage unit, and \( X_i \), \( Y_i \) are the charge and discharge state of the energy storage unit respectively, among them, \( X_i \in \{0,1\} \), \( Y_i \in \{0,1\} \).

Considering that the energy storage unit cannot be charged and discharged at the same time at the same time, the following constraints need to be satisfied.

\[
X_i \cdot Y_i = 0
\]

(9)

2) Energy storage unit power constraints

\[
\begin{align*}
P_{\text{ch,max}} & \leq P_{\text{ch},i} \leq 0 \\
0 & \leq P_{\text{dis},i} \leq P_{\text{dis,max}}
\end{align*}
\]

(10)

where \( P_{\text{ch,max}} \), \( P_{\text{dis,max}} \) are the maximum and minimal charge and discharge power of energy storage unit respectively.

3) Energy storage unit charge and discharge depth constraints

\[
SOC_{\text{min}} \leq SOC \leq SOC_{\text{max}}
\]

(11)

where \( SOC_{\text{max}} \), \( SOC_{\text{min}} \) are the maximum and minimal state of charge of energy storage unit respectively.

4) Energy storage unit charge and discharge time constraints
\[
\begin{align*}
&\sum_{r=1}^{T}|X_{r+1} - X_r| \leq N_1 \\
&\sum_{r=1}^{T}|Y_{r+1} - Y_r| \leq N_2
\end{align*}
\]

where \( N_1, N_2 \) are the maximum charge and discharge times of energy storage unit respectively.

### 3.3. Solution of multi-objective optimization model

#### 3.3.1. Dynamic inertia weight coefficient

This paper uses dynamic inertia weight coefficient to improve, and the formula is as follows.

\[
w = \left(\frac{w_{\text{max}} - w_{\text{min}}}{d_{\text{max}}}\right) \cdot d
\]

where \( w \) is the weighting factors that affect the speed of particles, \( w_{\text{max}}, w_{\text{min}} \) are the maximum and minimum values of \( w \) respectively, and \( d, d_{\text{max}} \) are the current and maximum number of iterations respectively.

#### 3.3.2. Asynchronously changing learning factors

In the early stage of optimization, the particles have strong self-learning ability and weak social learning ability, and strengthen the global search ability; in the later stage, the particles have strong social learning ability and weak self-learning ability, which is conducive to convergence to the global optimal. The learning factor asynchronous change formula is as follows.

\[
c_1 = c_{1,\text{ini}} + \left(\frac{c_{1,\text{fin}} - c_{1,\text{ini}}}{d_{\text{max}}}\right) \cdot d
\]
\[
c_2 = c_{2,\text{ini}} + \left(\frac{c_{2,\text{fin}} - c_{2,\text{ini}}}{d_{\text{max}}}\right) \cdot d
\]

where \( c_{1,\text{ini}}, c_{2,\text{ini}} \) are the initial values respectively, and \( c_{1,\text{fin}}, c_{2,\text{fin}} \) are the final values respectively.

#### 3.3.3. Calculate satisfaction with non-inferior solutions

This paper uses satisfaction to measure a non-inferior solution, and defines the satisfaction formula for each non-inferior solution as follows.

\[
\mu_{f_z} = \begin{cases} 
1 & f_{z}^{\min} < f_z < f_{z}^{\max} \\
\frac{f_{z}^{\max} - f_z}{f_{z}^{\max} - f_{z}^{\min}} & f_{z}^{\min} < f_z \leq f_{z}^{\min} \\
0 & f_{z}^{\max} \leq f_z
\end{cases}
\]

where \( \mu_{f_z}, f_z \) are the satisfaction standard and value of the objective function \( z \) respectively, and \( f_{z}^{\max}, f_{z}^{\min} \) are the maximum and minimum value of the objective function \( z \) respectively.

### 4. Simulation

#### 4.1. Simulation example description
The day-to-day forecast data of wind power, photovoltaic, conventional thermal power units and loads in Turpan is shown in Figure 1.

The type of energy storage selects the large-scale lithium iron phosphate battery pack that has been widely used. The specific parameters are shown in Table 1. The unit cost of energy storage is 50 yuan/(MWh), and the battery pack SOC is 0.5 at the initial moment.

| E/(MWh) | P/MW     | effectiveness | SOC   | N1 \ N2 |
|---------|----------|---------------|-------|---------|
| 14.0056 | (±) 2.80112  | 0.95   | 0.9(0.1) | 2       |
| 21.1242 | (±) 4.22484  | 0.95   | 0.9(0.1) | 2       |
| 19.1481 | (±) 3.82962  | 0.95   | 0.9(0.1) | 2       |
| 19.8166 | (±) 3.96332  | 0.95   | 0.9(0.1) | 2       |

The electricity revenue of the energy storage system is realized through the peak and valley electricity prices in the region. When 13:00-15:00/19:00-22:00 are the peak, the electricity price is 1149 yuan/MWh; When 1:00-8:00 are the valley, the electricity price is 782 yuan/MWh; The electricity price at other times is 414 yuan/MWh.

4.2. Analysis of simulation results
This paper compares the results of calculation examples after disordered charge and discharge of the energy storage unit (Mode 1) and the optimized operation method proposed in this paper (Mode 2).

4.2.1. Comparative analysis of system economic cost and network loss
The simulation results show that the system economic cost is inversely proportional to the network loss, and there is a conflicting relationship. The simulation results of system economic cost and network loss is shown in Figure 2.

Figure 1. System forecast data.

Figure 2. Comparison of system economic cost and network loss Pareto solution set.
According to formula (16), a set of solutions is selected from the Pareto solution set according to satisfaction as the global optimal solution. The results are shown in Table 2.

Table 2. Comparison of Pareto's cutting-edge optimization results.

| Mode | System economic cost/ yuan | Network loss/ MW |
|------|---------------------------|------------------|
| 1    | 751                       | 867              |
| 2    | 735                       | 845              |

In this paper, by optimizing the operation of multi-point energy storage units, the total economic cost of the system is reduced by 2.13%, and the network loss is reduced by 2.54%. It can be seen that the proposed method significantly improves the economic benefits of the system.

4.2.2. Analysis of the effect of suppressing power fluctuation

As shown in Figure 3, the figure shows the comparison of the smoothing effect in different models.

![Figure 3. Comparison of the effect of suppressing power fluctuation.](image)

In this paper, the absolute average value of the higher-level exchange power is used to evaluate the smoothing effect. The formula is as follows.

$$\bar{dp} = \frac{1}{24} \sum_{t=1}^{24} \left| P_{\text{line},t} - P_{\text{avgline}} \right|$$

(17)

where $\bar{dp}$, $P_{\text{avgline}}$ are the absolute average and absolute value of the superior exchange power, respectively.

The calculation shows that $\bar{dp}$ is 119MWh before optimization and 114MWh after optimization, with a decrease of 4.2%. It can be seen that by optimizing the energy storage charging and discharging power, this paper suppresses the fluctuation of the upper-level exchange power, which is conducive to the safe and stable operation of the regional power grid.

4.2.3. Analysis of the effect of wind power and photovoltaic power consumption

Figure 4 shows the comparative analysis of the wind power and optoelectronic power consumption in different models. The calculation shows that the total outflow of superior exchange power is 1285MWh before optimization and 1184MWh after optimization. There is a significant difference in the exchange power sent by the superior before and after the optimization, which is precisely due to the optimization of the regional operation, which enhances the wind and solar energy absorption capacity.
Figure 4. Comparison of the effect of wind power and photovoltaic power consumption.

4.2.4. Battery output plan
The state of charge of the battery changes as shown in Figure 5.

During the operating cycle, the battery charge and discharge states are basically two charge and two discharge, and the charge and discharge states are alternately less. The battery avoids deep charge and discharge, reduces life loss, helps extend the life of the battery, and reduces the battery cost.

5. Conclusion
This paper studies multi-objective optimal scheduling for improving renewable energy consumption considering energy storage participation. And taking the actual area of Xinjiang, China as an example, the simulation result shows that the method proposed in this paper improves the economic benefits of the regional power grid, reduces system power fluctuations, and improves the capacity of wind and solar absorption.

Acknowledgments
This work is supported by State Grid Xinjiang Electric Power Co., Ltd. (No. 5230DK180018).

References
[1] Reddy S S. Optimal scheduling of thermal-wind-solar power system with storage[J]. Renewable Energy, 2017, 101: 1357-1368.
[2] Ju L W, Tan Z F, Yuan J, et al. A bi-level stochastic scheduling optimization model for a virtual power plant connected to a wind–photovoltaic–energy storage system considering the uncertainty and demand response[J]. Applied Energy, 2016, 171: 184-199.
[3] Nguyen C, Lee H, Chun T. Cost optimized battery capacity and short-term power dispatch control for wind farm[J]. IEEE Transactions on Industry Applications, 2015, 51(1): 595-606.
[4] Chen Y, Smedley K. Three-phase boost-type grid-connected inverter[J]. IEEE Transactions on Power Electronics, 2008, 23(5): 2301-2309.
[5] Nick M, Cherkaoui R, Paolone M. Optimal planning of distributed energy storage systems in active distribution networks embedding grid reconfiguration[J]. IEEE Transactions on Power Systems, 2017, PP(99): 1-1.

[6] Liu Y Y, Tan S M, Jiang C W. Interval optimal scheduling of hydro-pv-wind hybrid system considering firm generation coordination[J]. IET Renewable Power Generation, 2017, 11(1):63-72.

[7] Sorouei A, Siano P, Keane A. Optimal DR and ESS scheduling for distribution losses payments minimization under electricity price uncertainty[J]. IEEE Transaction on Smart Grid, 2015, 7(1): 261-272.

[8] Golshannavaz S, Afsharnia S, Aminifar F. Smart distribution grid:optimal day-ahead scheduling with reconfigurable topology[J]. IEEE Transactions on Smart Grid, 2014, 5(5): 2402-2411.