Optimal dispatching and game analysis of power grid considering demand response and pumped storage

Xingquan Ji, Yao Li, Yongjin Yu and Shuxian Fan
College of Electrical Engineering and Automation, Shandong University of Science and Technology, Qingdao, People's Republic of China

ABSTRACT
In order to achieve the goal of economical and low carbonization while optimizing the dispatching of power system, an optimization model for the joint dispatch of wind power and pumped storage is established which considers the demand response with the goal of minimizing the cost of power generation and carbon emissions. The branch and bound algorithm is employed to solve the multi-objective optimization model. A two–player zero-sum game model is formulated to balance the multiple optimization goals, and the multi-objective optimization problem is converted to a single-objective optimization problem with the weighted coefficients. The case studies show that both the cost of power generation and the carbon emissions of the system have decreased after the introduction of demand response and pumped-storage units, and the benefits of co-scheduling are obvious.

1. Introduction
With the continuous increase in electricity demand and the increasing pressure on environmental resources, operation and scheduling technologies of power system considering energy saving and emission reduction have drawn high attention in recent years. Under the premise of ensuring the reliability of power supply, reducing the share of fossil energy consumption and carbon emission intensity as much as possible plays an important role in the sustainable development of the power industry (Zhang et al., 2016).

Lamadrid et al. (2015) presented a security constrained optimal power flow formulation to reduce carbon dioxide (CO₂) emissions. Under the condition of large-scale renewable energy generation integrated into power grid, it’s difficult to meet the fast-growing demand of new energy grid-connection only relying on generation-side scheduling. Demand response (DR) and demand-side resources can play important roles in the future electricity market (Kim & Giannakis, 2017). DR could provide zero carbon power generation and spinning reserve for the system, which has a positive effect on improving the safety of the power grid, reducing the operation cost and promoting the consumption of clean energy. In electricity market, DR can be divided into price-based DR and incentive-based DR. DR and energy storage system were introduced (Paterakis, Erdinc, Bakirtzis, & Catalao, 2015; Li et al., 2017) to analyze the optimal scheduling of wind power system, which can improve the utilization efficiency of wind power by its collaborative effects. Aihara et al. (2011) and You, Xiong, and Chang (2013) analyzed the joint scheduling of pumped-storage power stations and distributed power sources in multiple aspects. Operation strategies were developed based on wind power, intermittent and uncontrollable photovoltaic power generation. The pumped storage power station can effectively increase the capacity of the power grid for peak shaving, valley filling, and emergency backup, which is conducive to maintain the dynamic balance of system supply and demand. Differential evolution algorithm and heuristic algorithm (Peng, Sun, Guo, & Liu, 2012; Damodaran, Sunil Kumar, & Sciubba, 2018) are used to solve the wind storage system model. These algorithms can obtain a better solution set, but the selection and optimization of the weight coefficients have not been specifically considered. As a method of applied mathematics, game theory has obvious advantages in dealing with multi-party decision problems, which has been used in power market and economic dispatching. Chuang, Wu, and Varaiya (2001) applied game theory to solve the bidding decision problem in power trading. Five game models of wind-light-storage were proposed (Wang, Zhu, & Dong, 2011), and the impact of the corresponding models on Nash equilibrium and returns was discussed. However,
the application of non-cooperative games to the optimization of multiple types of unit output was not considered. In, the joint scheduling problem of wind storage systems and the research on the scheduling of regional power system through master-slave game theory were mainly analyzed (Li, Dang, Dong, & Zhou, 2015; Yuan, Ma, Sun, Chen, & Gao, 2017). Strategy set was generated by using master-slave game theory to improve the balance and stability of benefits distribution.

Considering the output characteristics of various units, we propose an optimal dispatch model that considers DR for power systems containing wind power and pumped storage units with the constraints such as the DR capacity, the load reduction, the system reserve capacity, and the start and stop time of units. The impact of wind power, DR, and the pumped storage power station on the optimization of system scheduling is analyzed. The branch and bound algorithm is used to solve the model, the weighted coefficient method is used to determine the target weights, and the optimal power generation plan is obtained in order to achieve a win-win result of economic and environmental benefits.

2. Optimal scheduling model considering demand response

Minimization of generation cost and carbon emissions are taken as the objective function. The cooperative scheduling model which combines the pumped storage units and incentive-based DR is as follows:

2.1. Objective function

2.1.1. The cost of power generations

The objective is to minimize the total operating cost of thermal power units and the cost of demand response within the scheduling period:

$$\min F = \min(F_G + F_{DR} + F_{PS})$$

where $F_G$ is the power generation cost of thermal power units which includes the fuel cost, the startup cost, and the shutdown cost; $F_{DR}$ is the invoking cost of demand response; $F_{PS}$ is the invoking cost of pumped storage power station.

The power generation cost of thermal power units can be expressed as:

$$F_G = \sum_{t=1}^{T} \sum_{i=1}^{N} [C_{Ni} + S_{i,t}]$$

where $T$ is the scheduling cycle; $N$ is the number of thermal power units; $C_{Ni}$ is the fuel cost of unit $i$; $S_{i,t}$ is the startup and shutdown cost of unit $i$ at period $t$.

The cost of DR can be expressed as:

$$F_{DR} = \sum_{t=1}^{T} \sum_{j=1}^{N_{DR}} (\lambda_j P_{DR,j} Z_{jt})$$

where $N_{DR}$ is the number of demand response resources; $P_{DR,j}$ is the virtual power generated by the DR equipment at period $t$; $\lambda_j$ is the compensation price of the DR equipment; $Z_{jt}$ is a 0–1 variable which indicates the status of the DR device, (on = 1, off = 0).

The cost of pumped storage unit can be expressed as:

$$F_{PS} = \sum_{t=1}^{T} (\mu_k P_{PS,k} M_{k,t})$$

where $P_{PS,k}$ is the power generated by the pumped storage unit at period $t$; $\mu_k$ is the pumping price of pumped storage unit; $M_{k,t}$ is a 0–1 variable which indicates the status of the pumped storage power station, (on = 1, off = 0).

$$C_{Ni} = (a_i P_{Gi,t}^2 + b_i P_{Gi,t} + c_i) u_{it}$$

where $P_{Gi,t}$ is the active power of unit $i$ at period $t$; $a_i$, $b_i$, and $c_i$ are the power generation cost parameters; $u_{it}$ is a 0–1 variable which indicates the status of unit $i$ in period $t$ (on = 1, off = 0).

$$S_{it} = \begin{cases} S_{hot,i} & T_{i,t}^{off} \leq T_{i,t} \leq T_{i,t}^{off} + T_{cold,i} \\ S_{cold,i} & -T_{i,t} > T_{i,t}^{off} + T_{cold,i} \end{cases}$$

where $S_{hot,i}$ and $S_{cold,i}$ are respectively the thermal startup cost and the cold start cost of the thermal power unit; $T_{i,t}^{off}$ is the minimum downtime of unit $i$; $T_{i,t}$ is the continuous operation time or continuous shutdown time of the thermal power unit $i$ in period $t$; $T_{cold,i}$ is the cold start time of the thermal power unit $i$.

2.1.2. Carbon emissions

$$E = \sum_{t=1}^{T} \sum_{i=1}^{N} [(\alpha_i + \beta_i P_{Gi,t} + \gamma_i P_{Gi,t}^2) u_{it}]$$

where $\alpha_i$, $\beta_i$, and $\gamma_i$ are the carbon emission coefficients of the generator $i$ respectively.

2.2. Constraints

The system operation constraints, thermal power unit operation constraints, technical constraints of pumped-storage units, and technical constraints of DR equipment should be preserved in optimal scheduling.

(1) Power balance constraint.

$$\sum_{i=1}^{N} u_{it} P_{Gi,t} + P_{h,t} + P_{p,t} + \sum_{w=1}^{N_w} P_{w,t} = P_t + \sum_{j=1}^{N_{DR}} Z_{jt} P_{DR,j}$$

where $P_{h,t}$ is the power generated by the pumped-storage power station during period $t$; $P_{p,t}$ is the pumping
power; $P_{w,t}$ is the power generated by the wind turbine during period $t$; and $P_t$ is the total load demand of the system during period $t$.

(2) Spinning reserve constraint.

$$\sum_{i=1}^{N} u_{t,i} P_{G,i} + \sum_{j=1}^{NDR} Z_{i,t} P_{DR,i,t} \geq P_t + R_{d,t} + R_{w,t}$$  (9)

where $R_{d,t}$ is the stand-by reserve capacity for the load, and $R_{w,t}$ is the stand-by reserve capacity for increased wind power.

(3) Power flow constraint.

$$\left| \frac{\theta_{ij} - \theta_{ij}}{x_{ij}} \right| \leq f_{ij,\max}$$  (10)

where $\theta_{ij}$ and $\theta_{ij}$ are the voltage phase angles of node $i$ and node $j$ respectively in period $t$; $x_{ij}$ is the branch impedance; $f_{ij,\max}$ is the upper limit of transmission power.

(4) Minimum on and off time constraints.

$$\begin{cases} (u_{t,i-1} - u_{t,i})(T_{i,t-1}^{on} - T_{i,t}^{on}) \geq 0 \\ (u_{t,i} - u_{t,i-1})(T_{i,t}^{off} - T_{i,t-1}^{off}) \geq 0 \\ \end{cases}$$  (11)

where $T_{i,t}^{on}$ is the minimum on time of unit $i$; $T_{i,t}^{on}$ is the cumulative on times till period $t$; $T_{i,t}^{off}$ is the cumulative off time till period $t$.

(5) Maximum and minimum output limits of thermal power units and wind turbines.

$$p_{G,i,t}^{min} \leq P_{G,i,t} \leq p_{G,i,t}^{max}$$  (12)

$$p_{W,j,t}^{min} \leq P_{W,j,t} \leq p_{W,j,t}^{max}$$  (13)

where $p_{G,i,t}^{max}$ and $p_{G,i,t}^{min}$ are respectively the upper and lower power limits of the thermal power unit in period $t$, $p_{W,j,t}^{max}$ and $p_{W,j,t}^{min}$ are respectively the upper and lower power limits of the wind turbine at period $t$.

(6) The constraints of pumped storage unit. It mainly includes the upper and lower limits of output, energy storage constraints and state constraints:

$$P_{h,t}^{min} \leq P_{h,t} \leq P_{h,t}^{max}$$  (14)

$$P_{p,t}^{min} \leq P_{p,t} \leq P_{p,t}^{max}$$  (15)

$$E_{t+1} = E_t + \Delta t (\eta_p P_{p,t} - \frac{P_{h,t}}{\eta_k})$$  (16)

$$E_t^{min} \leq E_t \leq E_t^{max}$$  (17)

$$P_{h,t} \times P_{p,t} = 0$$  (18)

where $E_t$ is the upper reservoir energy storage of the pumped storage power station in period $t$; $E_0$ is the initial energy storage of the pumped storage power station; $\Delta t$ is the scheduling duration; $\eta_p$ and $\eta_k$ are respectively the pumping efficiency and power generation efficiency of the pumped storage power station. Equation (17) is a state constraint, which indicating that the pumped storage power station can only be in a working state of pumping or generating electricity at any time (Xueling, Changming, & Huang, 2010).

(7) The ramp rate limit of thermal power units.

$$P_{G,i,t}^{down} \leq P_{G,i,t} - P_{G,i,t-1} \leq P_{G,i,t}^{up}$$  (19)

where $P_{G,i,t}^{up}$ and $P_{G,i,t}^{down}$ are respectively the ramp up rate and the ramp down rate of unit $i$.

(8) DR constraints. The form of DR includes changing the power consumption mode of the user, enhancing electricity efficiency of the terminal, and reducing the power consumption of the terminal. It can be regarded as a virtual generator which participates in system scheduling. The corresponding constraints are as follows:

Capacity constraint:

$$P_{DR,i} \leq P_{DR,i} \leq P_{DR,i}^0$$  (20)

Load reduction constraint:

$$0 \leq \Delta L_t \leq \Delta L_t^{max} Z_{i,t}$$  (21)

where $\Delta L_t^{max}$ is the maximum reduction of load at period $t$.

Up and down time constraints:

$$\frac{T_{on}^{DR,i,t-1} - T_{on}^{DR,i,t}}{L_t} (Z_{i,t-1} - Z_{i,t}) \geq 0$$  (22)

$$\frac{T_{off}^{DR,i,t-1} - T_{off}^{DR,i,t}}{L_t} (Z_{i,t-1} - Z_{i,t}) \geq 0$$  (23)

where $T_{on}^{DR,i,t}$ and $T_{off}^{DR,i,t}$ are the minimum up and down time of DR respectively.

3. Optimization process and solution

3.1. Solution algorithm

Considering that the calculation efficiency of mixed integer linear programming (MILP) is much faster than mixed integer quadratic programming (MIQP), the model established above is linearized and transformed into MILP model (Zhang, Che, & Wu, 2018). Then the priority list method is introduced in the process of solving the MILP model with the branch and bound method (Franco, Rider, & Romero, 2017).

The fuel cost function can be accurately approximated by a set of piecewise blocks. Figure 1 shows the fuel cost curve of the thermal unit which is divided into $L$ segments for linearization.
The objective function is linearized as:

$$\min F(u_{it}, P_{G_{li}}) = \sum_{l=1}^{N} \sum_{t=1}^{T} \left( \sum_{i=1}^{L} K_{li} P_{G_{li}} + u_{it} c_{i} \right)$$  \hspace{1cm} (24)$$

where $K_{li}$ is the slope of section $l$ after the linearization of the coal cost curve; $P_{G_{li}}$ is the output of unit $i$ at section $l$ in period $t$; $L$ is the number of sections. The piecewise linear function is approximately the same as the nonlinear function if enough segments are used. The carbon emission objective function is linearized in the same way.

The up and down time constraint is linearized as follows:

$$\sum_{t=t}^{a(T_{i}^{on})} u_{it} \geq (u_{it} - u_{i,t-1}) b(T_{i}^{on}) \hspace{1cm} t \geq 2$$  \hspace{1cm} (25)$$

$$\sum_{t=t}^{a(T_{i}^{off})} (1 - u_{it}) \geq (u_{i,t-1} - u_{it}) b(T_{i}^{off}) \hspace{1cm} t \geq 2$$  \hspace{1cm} (26)$$

$$\sum_{t=1}^{T_{i}^{on} - T_{i}^{0}} u_{it} \geq T_{i}^{on} - T_{i}^{0}$$  \hspace{1cm} (27)$$

$$\sum_{t=1}^{T_{i}^{off} + T_{i}^{0}} (1 - u_{it}) \geq T_{i}^{off} + T_{i}^{0}$$  \hspace{1cm} (28)$$

where $a(T_{i}^{on}) = \min\{t + T_{i}^{on} - 1, T\}$ and $b(T_{i}^{on}) = \min\{T_{i}^{on}, T - t + 1\}$. $T_{i}^{0}$ is the initial up and down time of unit $i$, $T_{i}^{0} < 0$ indicates the continuous down time of the unit $i$, and $T_{i}^{0} > 0$ indicates the continuous running time.

The state variable $u_{it}$ is slacked to $0 \leq u_{it} \leq 1$. The priority list method is used to describe the uncertain start-stop status variable. The order is adjusted according to the sequence of the minimum continuous up and down time constraints and the spinning reserve constraint, and the unit to be determined is found. The last starting unit is the critical one, and the adjacent units are expanded to be the uncertain units based on the critical unit (Abujarad, Mustafa, & Jamian, 2016). After the adjustment, the two constraints are satisfied, and the branch and bound method is then used to solve the uncertain status unit.

With the branching, delimitation, and pruning, steps of the branch and bound method, the discrete variable is approximated to an integer solution by decomposing the feasible region continuously (Ozturk, Begen, & Zaric, 2017). The variable element dichotomy method is used for branching. As shown in Figure 2, $x_{i}$ is a non-integer variable, and $\lfloor x_{i} \rfloor$ is the largest integer which is not less than $x_{i}$.

Each branch variable is simply decomposed into $0 \leq x_{i} \leq 1$ and $1 \leq x_{i} \leq 1$, which means their value are set to 0 and 1 respectively. With the same number of branching, a same-level sub-problem is obtained from the original problem, and the optimal value of each branch which satisfies the integer constraint is taken as the lower bound to determine the reservation of the branch and the choice of pruning (Kolpakov, Posypkin, & Sin, 2017). If the branch variable is the state variable of the unit $i$, the sub-problem with a value of 0 will also be pruned. Pruning is an important step which can improve the efficiency of algorithm.

The computational complexity of the branch and bound method is generally less than the enumeration method as it only searches within the feasible domain. In this paper, the branch and bound method is combined with the priority list method to solve the mixed integer programming model.

### 3.2. Weighted method based two-player zero-sum game

The economic attributes of power generation costs and the environmental attributes of carbon emissions are often inconsistent. Coal-fired units are characterized by lower overall costs and higher carbon emissions. On the other hand, the cost of new energy generation is high, and the carbon emissions are negligible. Economic goals and environmental goals are difficult to balance. The gains of one side are the losses of the other, and the two sides constitute an antagonistic situation. Therefore, it can be...
seen as a two-player zero-sum game (Greiner, Periaux, & Emperador, 2016).

We adopt a linear weighted method based on the two person zero-sum game. The weight coefficient is determined by the Nash equilibrium of the hybrid game strategy, which overcomes the limitation of the subjectivity of the decision makers by the traditional weighted coefficient method (Lou, Hong, Xie, Shi, & Johansson, 2016). This model has two objective functions, the cost of power generation and carbon emissions, denoted as $f_1$ and $f_2$, and the decision variable is the output of units at each time period. The power generation and the nature are recorded as player 1 and player 2, the strategy set of player 1 is $s_i \in \{s_1, s_2, \cdots, s_n\}$, and the strategy set of player 2 is $x_j \in X$. Players select a solution as a strategy from the optimal solution set obtained from each of the individually optimized targets. Due to the conflict between the two objective functions, their payoff values are opposite.

In the matrix shown in Table 1, payoff $f_{ij}(x_j)$ indicates the expected payoff when player 1 selects strategy $s_i$ and player 2 selects strategy $x_j$. As the dimensions of each goal in the multi-objective optimization problem are different, the goals are normalized as:

$$
f_{ij}' = \frac{f_{ij}(x_j)}{f_{ii}} \quad i, j = 1, 2, \cdots, n
$$

Suppose that $\theta_i$ is the probability that player 1 uses strategy $s_i$, and $\eta_j$ is the probability that player 2 uses strategy $x_j$. The expected payoff of player 1 can be expressed as:

$$
F = \sum_{i=1}^{n} \sum_{j=1}^{n} f_{ij}' \theta_i \eta_j
$$

The two-player zero-sum game model can be expressed as:

$$
\max_{\eta} \min_{\theta} F = \min_{\theta} \max_{\eta} F
$$

s.t. \quad \sum_{i=1}^{n} \theta_i = 1 \quad \theta_i \geq 0

\sum_{j=1}^{n} \eta_j = 1 \quad \eta_j \geq 0

The solution of the above model can be equivalent to the solution of the following two linear programming problems:

$$
\begin{align*}
\min & \quad \sum_{i=1}^{n} p_i \\
\text{s.t.} & \quad p_i \geq 0, i = 1, 2, \cdots, n \\
& \quad \sum_{i=1}^{n} f_{ij}' p_i \geq 1, j = 1, 2, \cdots, m
\end{align*}
$$

$$
\begin{align*}
\max & \quad \sum_{j=1}^{m} q_j \\
\text{s.t.} & \quad q_j \geq 0, j = 1, 2, \cdots, m \\
& \quad \sum_{j=1}^{m} f_{ij}' q_j \leq 1, i = 1, 2, \cdots, n
\end{align*}
$$

Solve the above optimization problems, we can get the optimal payment as:

$$
F^* = \frac{1}{\sum p_i^*} = \frac{1}{\sum q_j^*}
$$

The Nash equilibrium solution is:

$$
\begin{align*}
\theta_i^* &= F^* p_i^* \\
\eta_j^* &= F^* q_j^*
\end{align*}
$$

The weight of each goal of the original optimization problem can be obtained:

$$
\theta_i' = \frac{\theta_i}{f_{ii} \sum_{i=1}^{n} (\theta_i/f_{ii})}
$$

Figure 3 shows the flow chart of the proposed algorithm.

| Table 1. The Payoff Matrix of Player 1 |
|--------------------------|-----------------|-----------------|
| Players                 | $x_1$           | $x_m$           |
| $s_1$                   | $f_{s_1}(x_1)$  | $f_{s_1}(x_m)$  |
| $s_2$                   | $f_{s_2}(x_1)$  | $f_{s_2}(x_m)$  |

Figure 3. Flow chart of the algorithm.
4. Case studies

4.1. Basic data

The IEEE-39 system with 10 generators (Ongsakul & Petcharak, 2004) shown in Figure 4 is used to illustrate the validity of the proposed method. A pumped storage power station is installed at node 7, and two DR elements are connected at node 13 and node 21 respectively. The corresponding parameters are shown in Tables 2 and 3.

4.2. Optimization Results

Figure 5 shows the changes of the load shape after DR is implemented.

It can be seen from Figure 5 that users reduce their electricity consumption during peak hours to gain revenue, and increase electricity consumption during low peak hours. The load curve is smoothed and the system’s peak-to-valley difference is reduced by DR.

Reducing the power load is equivalent to generating surplus power to achieve similar effects to the actual power plant. Incentive-based DR can be seen as a virtual power plant in a broad category (Liu, Tang, & Xiang, 2017).

We consider two kinds of unit operation scenarios. In scenario 1, only the thermal power units are considered. In scenario 2, the DR and pumped storage units are introduced. Table 4 shows the power generation cost in different scenarios.

As can be seen from Table 4, after the introduction of pumped storage power stations and DR, although the response cost of DR is increased, the number and the cost of start-stop of the units will be reduced. Pumped storage unit plays the role of peak shaving, and the operating cost

| Scenario | Operating cost ($10^5$) | Start-stop cost ($10^5$) | Invoking cost ($10^5$) | Power generation cost ($10^5$) |
|----------|--------------------------|--------------------------|------------------------|-------------------------------|
| Scenario1 | 728.8                    | 52.7                     | 0                      | 781.5                         |
| Scenario2 | 678.7                    | 46.2                     | 51.3                   | 776.3                         |

Table 4. Optimization results in different scenarios.

Figure 6. Carbon emissions of thermal power units under different scenarios.

| Price ($/MW/h)$ | Maximum response power (MW) | Minimum response power (MW) | Maximum continuous response time (h) | Minimum continuous non-response time (h) |
|-----------------|-----------------------------|-----------------------------|--------------------------------------|-----------------------------------------|
| 5               | 20                          | 0                           | 4                                    | 6                                       |
| 6               | 15                          | 0                           | 6                                    | 6                                       |

Table 3. Parameters of DRs.

Table 5. Payoff matrix.

\[
\begin{array}{c|cc}
 & X_f & X_c \\
\hline
f_1(10^5$) & 7.762 \times 10^2 & 7.807 \times 10^2 \\
f_2(t) & 1.837 \times 10^4 & 1.789 \times 10^4 \\
\end{array}
\]
of the grid is reduced. In scenario 2, the total power generation cost of the system is reduced, which improves the economic efficiency of the system.

Figure 6 shows the comparison result of the carbon emissions of each thermal power unit in the two scenarios.

It can be seen that in scenario 2, DR can replace part of thermal power generation units as a zero-carbon virtual power generation resource. The pumped storage units produced peak shaving benefits and capacity benefits, which has reduced the peaking demand of the thermal power units and reduced coal consumption. The carbon emissions of each unit are reduced, which is beneficial to environmental protection.

The weighted coefficient method is then applied to the two-player zero-sum game. We denote the optimal power generation plan as $X_f$ and $X_c$. The power generation cost corresponding to each power generation plan is $f_1$ and $f_2$. Then the strategy of two virtual participants can be written as $f_1, f_2$ and $X_f, X_c$. The payment matrix of the zero-sum game is shown in Table 5:

The Nash equilibrium of the zero-sum game can be calculated from (32) and (33):

$$
\lambda_1 = 0.5041 \quad \lambda_2 = 0.4959
$$

The weight coefficient of each target can be determined according to (36):

$$
\lambda_1' = 0.7225 \quad \lambda_2' = 0.2775
$$

In this way, the original multi-objective problem can be transformed into a single-objective optimization problem:

$$
\min f(x) = \lambda_1' f_1(x) + \lambda_2' f_2(x)
$$

The optimal generation plan can be obtained by solving the above equation, and the output of each unit is shown in Table 6:

In the optimal dispatching scheme, the cost of electricity generation is $7.77 million and carbon emissions are 18,200 tons. Compared with the results of scenarios 1 and 2, both the carbon emissions and the cost of electricity generation have achieved a compromise solution, so the two players can obtain considerable benefits in this non-cooperative games.

5. Conclusions

In this paper, the total generation cost and carbon emissions of the power system were selected as the objective function, and the optimal dispatching model with DR and pumped storage power stations was formulated, which was solved by the branch and bound method. A linear weighting method based on a two-player zero-sum game was used to objectively determine the target weight coefficient, achieving the goal of energy conservation and environmental protection while ensuring economic efficiency.

Numerical studies showed that DRs and pumped storage units played important roles in peak load shifting, valley filling, generation efficiency enhancement, and emission reduction. The total power generation cost and carbon emissions were reduced through optimal dispatching. The application of the two-player zero-sum game weighted coefficient method achieved the balance between economic dispatch and energy saving dispatch.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Abujarad, S. Y. I., Mustafa, M. W., & Jamian, J. J. (2016). Unit commitment problem solution in the presence of solar and wind power integration by an improved priority list method. 6th International Conference on Intelligent and Advanced Systems, Kuala Lumpur, Malaysia, pp. 1–6.
Aihara, R., Yokoyama, A., Nomiyama, F., & Kosugi, N. (2011). Optimal operation scheduling of pumped storage hydro power plant in power system with a large penetration of photovoltaic generation using genetic algorithm. 2011 IEEE Trondheim PowerTech, Trondheim, pp. 1–8.

Chuang, A. S., Wu, F., & Varaiya, P. (2001). A game-theoretic master-slave game. 2011 IEEE Trondheim PowerTech, Trondheim, pp. 1–8.

Damodaran, S. K., & Sunil Kumar, T. K. (2018). Hydro-thermal-wind generation scheduling considering economic and environmental factors using heuristic algorithms. Energies, 11(353), 1–19.

Franco, J. F., Rider, M. J., & Romero, R. (2015). A mixed-integer linear programming model for the electric vehicle charging coordination problem in unbalanced electrical distribution systems. IEEE Transactions on Smart Grid, 6(5), 2200–2210.

Greiner, D., Periaux, J., Emperador, J. M., Galván, B., & Winter, G. (2016). Game theory based evolutionary algorithms: A review with Nash applications in structural engineering optimization problems. Archives of Computational Methods in Engineering, 24(4), 703–750.

Kim, S. J., & Giannakis, G. B. (2017). An online convex optimization approach to real-time energy pricing for demand response. IEEE Transactions on Smart Grid, 8(6), 2784–2793.

Kolpakov, R. M., Posypkin, M. A., & Sin, S. T. T. (2017). Complexity of solving the Subset Sum problem with the branch-and-bound method with domination and cardinality filtering. Automation and Remote Control, 78(3), 463–474.

Lamadrid, A. J., Shawhan, D. L., Murillo-Sanchez, C. E., Zimmerman, R. D., Zhu, Y., Tylavsky, D. J., … Dar, Z. (2015). Stochastically optimized carbon-reducing dispatch of storage generation and loads. IEEE Transactions on Power Systems, 30(2), 1064–1075.

Li, H., An, Q., Yu, B., Zhao, J., Cheng, L., & Wang, Y. (2017). Strategy analysis of demand side management on distributed heating driven by wind power. Energy Procedia, 105, 2207–2213.

Li, R., Dang, L., Dong, Z., & Zhou, H. (2015). Coordinated optimization of time-of-use price and dispatching model combining wind power and energy storage under guidance of master-slave game. Power System Technology, 39(11), 47–53.

Liu, J., Tang, H., Xiang, Y., Liu, J., & Zhang, L. (2017). Multi-stage market transaction method with participation of virtual power plants. Electric Power Construction, 38(3), 137–144.

Lou, Y., Hong, Y., Xie, L., Shi, G., & Johansson, K. H. (2016). Nash equilibrium computation in subnetwork zero-sum games with switching communications. IEEE Transactions on Automatic Control, 61(10), 2920–2935.

Ongsakul, W., & Petcharaks, N. (2004). Unit commitment by enhanced adaptive Lagrangian relaxation. IEEE Transactions on Power Systems, 19(1), 620–628.

Ozturk, O., Begen, M. A., & Zaric, G. S. (2017). A branch and bound algorithm for scheduling unit size jobs on parallel batching machines to minimize makespan. International Journal of Production Research, 55(6), 1815–1831.

Paterakis, N. G., Erdinc, O., Bakirtzis, A. G., & Catalao, J. P. S. (2015). Load-following reserves procurement considering flexible demand-side resources under high wind power penetration. IEEE Transactions on Power Systems, 30(3), 1337–1350.

Peng, C., Sun, H., Guo, J., & Liu, G. (2012). Dynamic economic dispatch for wind-thermal power system using a novel bi-population chaotic differential evolution algorithm. International Journal of Electrical Power & Energy Systems, 42(1), 119–126.

Su, X., Ji, C., Huang, X., Jia, D., & Guo, X. (2010). Optimizing operation of the hybrid pumped-storage power station between cascade reservoirs. Automation of Electric Power Systems, 34(4), 29–33.

Wang, S., Zhu, J., Dong, G., Zhang, Y., & Dai, J. (2011). A transmission network expansion planning based OPA model. Automation of Electric Power Systems, 35(20), 7–12.

You, W., Xiong, Y., & Chang, J. (2013). Joint power generation schedules of wind farms and pumped storage power stations based on load tracking. International Conference on Modelling, Identification & Control. Cairo, Egypt, pp. 153–157.

Yuan, T., Ma, T., Sun, Y., Chen, N., & Gao, B. (2017). Game-based generation scheduling optimization for power plants considering long-distance consumption of wind-solar-thermal hybrid systems. Energies, 10(9), 1–15.

Zhang, S., Che, A., Wu, X., & Chu, C. (2018). Improved mixed-integer linear programming model and heuristics for bi-objective single-machine batch scheduling with energy cost consideration. Engineering Optimization, 50(8), 1380–1394.

Zhang, N., Hu, Z., Dai, D., Dang, S., Yao, M., & Zhou, Y. (2016). Unit commitment model in smart grid environment considering carbon emissions trading. IEEE Transactions on Smart Grid, 7(1), 420–427.