Optimal scheduling modelling for wind power accommodation with compressed air energy storage and price-based demand response

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Abstract. Nowadays, price-based demand response (PDR) programs with compressed air energy storage (CAES) systems have been rapidly developed in China for wind power generation propagation. Based on this development trend, an optimal scheduling model considering thermal power units (TUs), wind power plants, PDR mechanisms and CAES plants is studied in this paper. Considering the factors of uncertainties in PDR, wind power output and electricity demand, a fuzzy power system optimal scheduling model for minimizing the sum of TUs operation cost, CAES plants cost and wind curtailment penalty is proposed. According to the fuzzy scheduling theory, the fuzzy chance constrains are converted into their clear equivalent forms. The simulation study is implemented with using the data from the Huntorf CAES plant, which can verify the feasibility and effectiveness of the optimal scheduling model. It is found that the use of CAES and PDR results in 11.1% reduction in thermal power units operation cost and 71.6% reduction in the penalty of wind curtailment.

1. Introduction

Wind power generation in China has been rapidly developed, due to its environment friendly and fossil fuel saving benefits [1]. However, the intermittency and uncertainty of wind power bring technical and economical challenges to power systems. This restrains the wind power propagation seriously [2]. Thus, how to utilize wind power with maintaining the power system reliability and maximizing economic benefits has attracted much attention.

Price-based demand response (PDR) mechanisms make consumers actively adjust their energy consumptions by adjusting electricity price [3]. It has been proven as an efficient way to mitigate wind power curtailment [4], power system operation economy [5] and power system security [6]. In 2012, the Chinese Ministry of Finance released an announcement: “the implementation of PDR mechanisms will be supported by Chinese government in financial” [7]. The PDR mechanism has now been in a period of rapid development in China.

Apart from demand response (DR) mechanisms, combining the wind power with energy storage devices is another effective way to address the wind power curtailment problem [8]. Among the available energy storage technologies, only pumped storage and compressed air

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energy storage (CAES) have commercial experience in large scale [9]. However, the wind power resources in China mainly concentrate in the northern area where the implementation of pump storage is restricted by geographical conditions. Therefore, the development of CAES in China is encouraged especially in this area. At present, there are two successfully commercial CAES plants in the world. The first is the Huntorf CAES plant in Germany and the second is the McIntosh CAES plant in US. Apart from this, several CAES plants are under construction [9]. In China, Institute of Engineering Thermophysics, Chinese Academy of Sciences has completed a 15 kW experimental system and a 1.5 MW demonstration system [1]. Tsinghua University, Chinese Electric Power Research Institute and Technical Institute of Physics and Chemistry of the Chinese Academy of Sciences have constructed a 500 kW non-supplementary fired CAES and finished the field tests in 2014 [1].

With the development trends of PDR mechanisms and CAES systems in China, the new system scheduling resources should not only consider thermal power units (TUs), but also consider PDR and CAES plants as well.

Currently, a significant amount of attention has been given to the scheduling of PDR. A power system day-ahead scheduling model considering the participation of PDR was proposed by Bie *et al* [10]. The proposed model is used to mitigate wind power curtailment. Wang, et al studied the day-ahead generation scheduling strategy considering DR in large-capacity wind power integrated systems, and the proposed strategy was proved to have ability of improving wind power accommodation rate [11]. A multi-stage robust optimization approach was developed to accommodate both wind power and DR uncertainties by Zhao *et al* [12].

Literatures on CAES plants participating in power system optimization scheduling are starting to grow. Daneshi and Srivastava studied the security-constrained unit commitment problem with wind generation and CAES, and the impact of CAES on economics, peak-load shaving, transmission congestion management, wind curtailment and environmental perspective was analysed [13]. An optimal operation scheduling strategy of wind power integrated with CAES was proposed by Abbaspour, which can improve the operational profits [14]. To realize the efficient utilization of large-scale wind power, Wang, et al proposed a thermal-wind-storage joint operation framework considering pumped storage and CAES [15].

However, there are few reports relevant to the study of scheduling strategies with considering both PDR mechanisms and CAES plants. Afshin, et al proposed a stochastic self-scheduling program for CAES of renewable energy sources based on a demand response mechanism, which can decrease the operation costs of TUs and CAES plants [16]. However, the PDR mechanisms were not taken as a scheduling resource in [16]. The wind power accommodation and the uncertainty of demand response rate were not considered as well.

This paper proposes a fuzzy optimal scheduling model considering the participation of CAES and PDR. The uncertainties of PDR, wind power output and electricity demand are involved in the model. The optimization objective of the model takes both system operation costs and wind power curtailment penalty into account. The developed model is validated through a simulation test. In addition, the impacts of different scheduling resources, PDR uncertainty and load self-elasticity coefficients on the optimal results are analysed through the case study.

2. Fuzzy optimal scheduling model considering CAES and PDR

2.1. Objective function

The optimization objective of the model is minimizing the sum of TUs operation cost, CAES plants cost and wind power curtailment penalty. It should be mentioned that the penalty of wind power curtailment is involved in the objective function for mitigating wind power curtailment. The mathematical model of the proposed objective function is defined by,

$$\min \sum_{t=1}^{T}(Cost_{\text{thermal},t} + Cost_{\text{CAES},t} + Cost_{\text{wind},t}) \tag{1}$$

where T is the total time periods. $Cost_{\text{thermal},t}$ and $Cost_{\text{CAES},t}$ represent the operation costs of TUs and CAES at time *t*, respectively. $Cost_{\text{wind},t}$ is the penalty of wind power curtailment at time *t*.

TUs operation cost is composed of the TU start-up cost and the TU fuel cost. It can be described by [16],

$$Cost_{\text{thermal},t} = \sum_{i=1}^{N_G}[(b_i P_{Gi,t} + c_i)u_{i,t} + S_i(1-u_{i,t-1})u_{i,t}] \tag{2}$$

where N_G is the number of thermal units. b_i and c_i are the coefficients of linear cost function of TU *i*. $P_{Gi,t}$ is the output power of TU *i* in a time period *t*. $u_{i,t}$ is the binary variable to indicate the state of TU *i*, when the TU is shut down, $u_{i,t}=0$, and when it is started up, $u_{i,t}=1$. S_i is the unit start-up cost of TU *i*.

The formulation of CAES operation cost is as follows [17]:

$$Cost_{\text{CAES},t} = \frac{Q_{\text{CAESG},t}}{A_{gas}\eta_{gas}} c_{gas} \tag{3}$$

where $Q_{\text{CAESG},t}$ is the heat from gas combustion during the generation process. η_{gas} is the combustion efficiency of natural gas. A_{gas} is the gas's calorific value. c_{gas} is the natural gas price.

The penalty of wind power curtailment is shown as follows:

$$Cost_{\text{wind},t} = \xi q_{Wcur,t} \tag{4}$$

where ξ is the unit penalty of wind power curtailment; $q_{Wcur,t}$ is the electricity of wind power curtailment.

2.2. Constraints

The power system constraints are described by (5)-(7). Constraint (5) enforces load balance. Constraints (6) and (7) ensure the system has sufficient positive spinning reserve capacity and negative spinning reserve capacity.

$$\sum_{i=1}^{N_G} u_{i,t}P_{Gi,t} + v_{G,t}P_{CAESG,t} + P_{Wf,t} = P_{fL,t} + \frac{\lambda_{\Delta qf,t}q_{0t}}{\Delta t} + v_{C,t}P_{CAESC,t} + \frac{q_{Wcur,t}}{\Delta t} \tag{5}$$

$$Cr\{\sum_{i=1}^{N_G} u_{i,t}\min(P_{Gi,\max}, P_{Gi,t}+R_{i,up}) + \tilde{P}_{W,t} + P_{CAESG,\max} \geq \tilde{P}_{L,t} + \frac{\tilde{\lambda}_{\Delta q,t}q_{0t}}{\Delta t} + \frac{q_{Wcur,t}}{\Delta t}\} \geq \beta \tag{6}$$

$$Cr\{\sum_{i=1}^{N_G} u_{i,t}\max(P_{Gi,\min}, P_{Gi,t}-R_{i,down}) + \tilde{P}_{W,t} \leq \tilde{P}_{L,t} + \frac{\tilde{\lambda}_{\Delta q,t}q_{0t}}{\Delta t} + \frac{q_{Wcur,t}}{\Delta t} + P_{CAESC,\max}\} \geq \beta \tag{7}$$

where $P_{CAESG,t}$ and $P_{CAESC,t}$ are the generating power and the compressing power of CAES at time *t* respectively. $v_{G,t}$ and $v_{C,t}$ are the binary variable to indicate the state of CAES system, when the CAES system is in generator state, $v_{G,t}=1$, and when it is in compressor state, $v_{C,t}=1$. Δt is unit scheduling period. $P_{Gi,\max}$ and $P_{Gi,\min}$ are the maximum and minimum output

powers of TU i. $R_{i,up}$ and $R_{i,down}$ are the ramp-up and ramp-down limits of TU i. $Cr\{A\}$ describes the credibility of occurrence of event A. β is the confidence level of the constraints. $P_{Wf,t}$ and $P_{fL,t}$ are the forecast wind power output and the forecast electricity demand at time t. $\tilde{P}_{W,t}$ and $\tilde{P}_{L,t}$ are the fuzzy description of wind power output and electricity demand, respectively. $\tilde{\lambda}_{\Delta q,t}$ is the fuzzy description of demand response rate at time t. $q_{0,t}$ is the original electricity demand at time t. The triangular membership parameters of $\tilde{P}_{W,t}$, $\tilde{P}_{L,t}$ and $\tilde{\lambda}_{\Delta q,t}$ are $\tilde{P}_{W,t}=((1-k_W)P_{Wf,t},P_{Wf,t},(1+k_W)P_{Wf,t})$, $\tilde{P}_{L,t}=((1-k_L)P_{Lf,t},P_{Lf,t},(1+k_L)P_{Lf,t})$ and $\tilde{\lambda}_{\Delta q,t}=((1\text{-}k_\lambda)\varepsilon_{tt}\lambda_{\Delta c,t},(1+k_\lambda)\varepsilon_{tt}\lambda_{\Delta c,t},)$ [18]. k_W, k_L and k_λ are the maximum forecast error ratios of wind power, load and demand response rate, respectively. $\lambda_{\Delta c,t}$ represents the change rate in price in a time period t. ε_{tt} is the load self-elasticity coefficient.

Constraints for TUs are described by (8)-(10). Constraint (8) is the TUs output limits. Constraints (9) enforce the ramping rate limits of each unit. Constraints (10) ensure up-time and down-time limits of each unit [13].

$$P_{Gi,\min} \le P_{Gi,t} \le P_{Gi,\max} \tag{8}$$

$$\begin{cases} P_{Gi,t} - P_{Gi,t-1} \le R_{i,up} \\ P_{Gi,t-1} - P_{Gi,t} \le R_{i,down} \end{cases} \tag{9}$$

$$\begin{cases} T_{i,t}^{on} \ge T_{i,\min}^{on} \\ T_{i,t}^{off} \ge T_{i,\min}^{off} \end{cases} \tag{10}$$

where $T_{i,t}^{on}$ and $T_{i,t}^{off}$ are the up-time and down-time of TU i at time t; $T_{i,\min}^{on}$ and $T_{i,\min}^{off}$ are the minimum up-time and down-time of TU i.

Wind power curtailment electricity constraint is shown as follows:

$$0 \le q_{Wcur,t} \le P_{Wf,t}\Delta t \tag{11}$$

Constraints for PDR are described by (12) and (13). Constraint (12) enforce the lower and upper limits of electricity price. Constraint (13) ensure the electricity demand is unchanged after the scheduling [18].

$$\lambda_{\Delta c,\min} \le \lambda_{\Delta c,t} \le \lambda_{\Delta c,\max} \tag{12}$$

$$\sum_{t=1}^{T} \lambda_{\Delta qf,t} q_{0t} = 0 \tag{13}$$

where $\lambda_{\Delta c,\min}$ and $\lambda_{\Delta c,\max}$ stand for the lower and upper limits of electricity price.

Constraints for CAES are described by (14)-(22). Constraints (14) and (15) ensure the upper and lower limits of compressors and generators in CAES. Constraint (16) enforces the pressure in the cavern within a reasonable range. Constraint (17) is used to prevent the CAES from being in generator and compressor status at the same time. Constraint (18) ensures the pressure difference limits. Constraints (19) and (20) ensure the relation between the average mass flow rate and power. Constraint (21) ensure the relation between the average mass flow rate and average pressure change rate. Constraint (22) ensures the relation between average pressure change rate and heat absorption [18,19].

$$P_{CAESC,\min} \le P_{CAESC,t} \le P_{CAESC,\max} \tag{14}$$

$$P_{CAESG,\min} \le P_{CAESG,t} \le P_{CAESG,\max} \tag{15}$$

$$p_{\min} \le p_t \le p_{\max} \tag{16}$$

$$v_{C,t} + v_{G,t} \le 1 \tag{17}$$

$$-\Delta p_{\max} \le p_{\mathrm{T}} - p_0 \le \Delta p_{\max} \tag{18}$$

$$\bar{\dot{m}}_{in,t} n_C \frac{\kappa}{\kappa - 1} R_g T_{Cin} (\pi_{opt,C}^{\frac{\kappa-1}{\kappa}} - 1) = P_{CAESC,t} \eta_C \tag{19}$$

$$\bar{\dot{m}}_{out,t} \eta_G n_G \frac{\kappa}{\kappa - 1} R_g T_{Gin} (\pi_{opt,G}^{\frac{\kappa-1}{\kappa}} - 1) = P_{CAESG,t} \tag{20}$$

$$\bar{\dot{p}}_t = \frac{R_g \kappa}{V} (T_{cain} \bar{\dot{m}}_{in,t} v_{C,t} + T_{ca0} \bar{\dot{m}}_{out,t} v_{G,t}) \tag{21}$$

$$\bar{\dot{m}}_{out,t} \Delta t c_p (T_{Gin} - T_{ca0})(1 - U_{re}) = Q_{CAESG.t} \tag{22}$$

where $P_{CAESC,\min}$ and $P_{CAESC,\max}$ are maximum and minimum compressing power of CAES respectively. $P_{CAESG,\min}$ and $P_{CAESG,\max}$ are maximum and minimum generating power of CAES respectively. $p_{\max}$ and $p_{\min}$ are the upper and lower limits of pressure in the cavern respectively. p_t is the air pressure in the cavern. p_0 and p_{T} are the pressure in the cavern before the start of the scheduling and after the end of the scheduling, respectively. $\Delta p_{\max}$ is the maximum tolerance of the pressure difference. $\bar{\dot{p}}_t$ is the air pressure changing rate at time *t*. $\bar{\dot{m}}_{in,t}$ and $\bar{\dot{m}}_{out,t}$ are the average mass flow rate of the incoming air from the compressor and the out-going air to the turbine, respectively. n_C and n_G are the stages number of the compressor and the turbine, respectively. κ is the heat capacity ratio of air. R_g is the ideal gas constant. η_C and η_G are the efficiency of the compressing process and the generating process, respectively. T_{Cin} and T_{Gin} are the inlet air temperature of compressor and turbine, respectively. $\pi_{opt,C}$ and $\pi_{opt,G}$ are the optimal pressure ratio of the compressor and the turbine, respectively. V is the volume of the cavern. T_{cain} is the inlet air temperature of cavern. T_{ca0} is the air temperature in the cavern at the beginning of the scheduling.

3. Solution methodology

The proposed optimization problem is a fuzzy chance constrained programming problem which cannot be solved directly by existing commercial optimization software because of the fuzzy chance constraints contained. To solve this problem, the fuzzy chance constraints, which are positive and negative spinning reserve capacity constraints, can be converted into the clear equivalent forms [18,20]. The constraints can be described as follow [20]:

$$(2-2\beta)(P_{L2,t}+\frac{\lambda_{\Delta q2,t}q_{0t}}{\Delta t}-P_{W2,t})+(2\beta-1)(P_{L3,t}+\frac{\lambda_{\Delta q3,t}q_{0t}}{\Delta t}-P_{W1,t})+$$
$$\frac{q_{Wcur,t}}{\Delta t}\le\sum_{i=1}^{N_G}u_{i,t}\min(P_{Gi,\max},P_{Gi,t}+R_{i,up})+P_{CAESG,\max} \quad (23)$$

$$(2-2\beta)(P_{L2,t}+\frac{\lambda_{\Delta q2,t}q_{0t}}{\Delta t}-P_{W2,t})+(2\beta-1)(P_{L1,t}+\frac{\lambda_{\Delta q3,t}q_{0t}}{\Delta t}-P_{W3,t})+$$
$$P_{CAESC,\max}+\frac{q_{Wcur,t}}{\Delta t}\ge\sum_{i=1}^{N_G}u_{i,t}\max(P_{Gi,\min},P_{Gi,t}-R_{i,down}) \quad (24)$$

After converting the constraints into their deterministic equivalent formulations, the optimal problem becomes a deterministic mixed integer linear programming (MILP) problem which can be solved by conventional optimization solver. CPLEX 12.6.3 have been widely used to solve the MILP problem due to its high efficiency and accuracy [10-13]. Therefore, CPLEX 12.6.3 is used to solve this problem in this paper.

4. Results and discussion

A system containing 10 TUs, a wind farm and a CAES plant is used to evaluate the performance of the proposed scheduling method. Additionally, the day ahead time-of-use price mechanism is assumed to be adopted in the system.

The parameters of the generators are given in [18]. The parameters of the CAES plant which are based on the real operation data from the Huntorf CAES plant are given in [17,19]. The scheduling horizon is 24 hours, and each scheduling time period is 1h. The 24 hours system load without the scheduling and the forecast wind power outputs are shown in figure 1 [18]. The maximum forecast error ratios of wind power, load and demand response rate are set to be 40%, 10% and 40%, respectively [18,19].

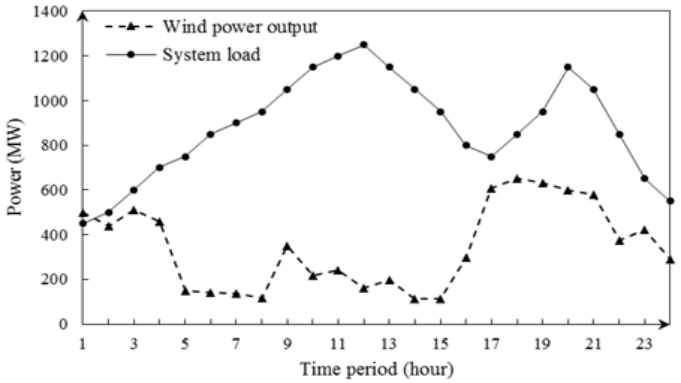

Figure 1. Curve of forecast wind power output and system load.

The upper and lower limits of electricity price change rates are set to be 0.5 and -0.5. We set the self-elasticity coefficient to be -0.2 [8]. The unit penalty of wind power curtailment is set to be 350 (CNY/MW.h). Assuming the heat recovery unit is not equipped in the CAES plat, so that $U_{re}=0$. The confidence level of spinning reserve constraints is set to be 0.95.

Four scenarios are studied to analyze the effects of different scheduling resources participating in scheduling.

Scenario1: there is no CAES plants and PDR programs in the system, the only scheduling resources are TUs

Scenario2: the scheduling resources are TUs and PDR resources.

Scenario3: the scheduling resources are TUs and the CAES plant.

Scenario4: the scheduling resources are TUs, PDR resources and the CAES plant.
Table 1 shows the costs of each scenario.

Table 1. Costs of each scenario.

Scenarios	Scenario1	Scenario2	Scenario3	Scenario4
Strat-up cost (CNY)	88080	70320	46980	75840
Fuel cost (CNY)	1675901	1606660	1514362	1491401
CAES operation cost (CNY)	/	/	17101	11009
Wind power curtailment penalty (CNY)	381395	371545	192045	108345
Total cost (CNY)	2145376	2048524	1770487	1686595

It is shown in table 1 that the start-up cost, the fuel cost, the wind power curtailment penalty and the total cost in scenario 2 and 3 are lower than the costs in scenario 1, and the costs in scenario 4 are the lowest among of all scenarios. The comparison of results of scenario 1 and 4 shows 11.1% reduction in TUs operation cost, 71.6% reduction in wind power penalty cost, and 21.4% reduction in total cost. It indicates that, the PDR mechanism and the CAES plant can bring benefits to system operation economics and wind power accommodation.

On the basic of scenario 2 and 4, the system with four different self-elasticity coefficients before and after considering PDR uncertainty is tested. The optimization results in scenario 2 are shown in table 2, while the results in scenario 4 are shown in table 3.

Table 2. Costs with different self-elasticity coefficients before and after considering PDR uncertainty based on scenario 2.

Self-elasticity coefficients		Start-up cost (CNY)	Fuel cost (CNY)	Wind power curtailment penalty (CNY)	Total cost (CNY)
Before considering PDR uncertainty	$\varepsilon_{tt}=-0.1$	66900	1618725	351945	2037569
	$\varepsilon_{tt}=-0.2$	61980	1585473	285795	1933247
	$\varepsilon_{tt}=-0.3$	61800	1574362	226295	1862456
	$\varepsilon_{tt}=-0.4$	61620	1566427	177645	1805692
After considering PDR uncertainty	$\varepsilon_{tt}=-0.1$	85800	1630783	375045	2091627
	$\varepsilon_{tt}=-0.2$	70320	1606660	371545	2048524
	$\varepsilon_{tt}=-0.3$	66480	1602322	333045	2001846
	$\varepsilon_{tt}=-0.4$	66960	1605789	315195	1987944

Table 3. Costs with different self-elasticity coefficients before and after considering PDR uncertainty based on scenario 4.

Self-elasticity coefficients		Start-up cost (CNY)	Fuel cost (CNY)	Wind power curtailment penalty (CNY)	CAES operation cost (CNY)	Total cost (CNY)
Before considering PDR uncertainty	$\varepsilon_{tt}=-0.1$	73020	1492956	114645	13603	1694223
	$\varepsilon_{tt}=-0.2$	72480	1483360	71945	11009	1638794
	$\varepsilon_{tt}=-0.3$	40800	1458953	70545	16134	1586431
	$\varepsilon_{tt}=-0.4$	40800	1456000	48845	11009	1556654

After considering PDR uncertainty	$\varepsilon_{tt}=-0.1$	72840	1492306	140895	13603	1719644
	$\varepsilon_{tt}=-0.2$	75840	1491401	108345	11009	1686595
	$\varepsilon_{tt}=-0.3$	41820	1474331	134595	11009	1661755
	$\varepsilon_{tt}=-0.4$	45180	1468261	110795	11009	1635245

From the results in tables 2 and 3, after consider PDR uncertainty, the total cost and wind power curtailment cost are greater than the relative costs before considering the PDR uncertainty. It indicates that, the PDR uncertainty has a negative effect on wind power accommodation and saving TUs operation costs. The main reason is that the power system needs more spinning reserve capacity because of the uncertainty of PDR.

It can also be seen that the total cost has a tendency to decrease as the absolute value of self-elasticity coefficient increases. However, the decreasing trend of total cost is weakened after considering PDR uncertainty.

From the comparison of tables 2 and 3, it can be observed that after the CAES plant participates in power system scheduling, the PDR uncertainty also has a negative effect on system operation economy and wind power accommodation, but this negative effect is reduced. This is mainly because that the CAES plant can provide spinning reserve capacity for the PDR uncertainty, so that the negative effect of the PDR uncertainty can be weaken.

5. Conclusion

A fuzzy optimal scheduling model considering TUs, wind power farms, CAES plants and PDR programs is proposed. The uncertainties of PDR, wind power output and electricity demand are considered in the model. After converting the fuzzy chance constraints into their clear equivalent forms, the conventional optimization solver can be used to solve the problem. With the simulation study and the numerical analysis, the following conclusions can be drawn:

- Using CAES and PDR results in 11.1% reduction in TUs operation cost and 71.6% reduction in wind power curtailment penalty.
- PDR uncertainty has a negative effect on wind power accommodation and saving TUs operation cost. Additionally, the total cost has a tendency to decrease as the absolute value of self-elasticity coefficient increases. However, the decreasing trend of total cost is weakened after considering the PDR uncertainty.
- The CAES plant can reduce the negative effect of PDR uncertainty.

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