J. Mod. Power Syst. Clean Energy (2015) 3(1):63–71
DOI 10.1007/s40565-014-0095-6

Low-carbon unit commitment with intensive wind power generation and carbon capture power plant

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Abstract The paper proposes a stochastic unit commitment (UC) model to realize the low-carbon operation requirement and cope with wind power prediction errors for power systems with intensive wind power and carbon capture power plant (CCPP). A linear re-dispatch strategy is introduced to compensate the wind power deviation from the spot forecast. The robust optimization technique is employed to obtain a reliable commitment plan against all realizations of wind power within the uncertainty set given by probabilistic forecast. The proposed model is validated with IEEE 39-bus system. The advantages of flexible CCPPs are compared to the normal coal-fueled plants and the impacts of robustness controlling are discussed.

Keywords Low-carbon unit commitment, Carbon capture and storage, Linear re-dispatch strategy, Robust optimization

1 Introduction

The global warming attracts more and more attentions in the recent few decades [1]. Relevant researches advocated that the excessive emission of greenhouse gases is the main cause [2]. As a result, the United Nations framework convention on climate change (UNFCCC) was proposed and Kyoto Protocol has been signed. According to the protocol, low-carbon development aiming to reduce CO_2 emission is essential for the contracting parties including China. In 2005, an intergovernmental panel on climate change (IPCC) special report [3] showed that the electrical power generation accounts for over 34% of the global CO_2 emissions owing to the popularity of fossil-fueled power plants. Hence, power system should be one of the main frontiers in the low-carbon revolution.

It can be noticed that there are two available solutions when it comes to low-carbon development in electric power generations. One is to control the CO_2 emission in the existing fossil-fueled plant, while the other one is to seek for alternative clean power sources. Therefore, the carbon capture and storage (CCS) technique is applied to absorb and seal the CO_2 produced by power plants while the renewable energy sources including wind and solar power are rapidly exploited throughout the world.

Undoubtedly, the integration of carbon capture power plant (CCPP) and renewable energy is bringing out new challenges and ideas to power system operation and dispatch. As for CCS technique, a mix-integer linear model for CCPP dispatch was proposed in [4], only considering the fixed CO_2 capture rate. The potential of flexible control in CCS consumption power was reported to swiftly adjust the net output of power plant in [5]. In [6], typical methods in flexible CCS control were summarized and the corresponding model was proposed for flexible CCPP in steady-state operation analysis. In [7] and [8], the optimal strategies were discussed to maximize the operation profits from flexible CCPPs and the results showed that premium profits may be obtained by properly adjusting the CO_2 capture rate according to the electricity and carbon prices. As for renewable energy, the focus is mainly on coping with the forecast errors. The scenarios, intervals, and risk index for the descriptions of wind power forecast errors were introduced in [9], and it is argued that forecast errors are inevitable and not negligible because of the stochastic nature of wind speed and the parameter uncertainties in the practical

CrossCheck date: 18 December 2014

Received: 3 October 2014 / Accepted: 30 December 2014 / Published online: 23 January 2015

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wind power curve. Consequently, the spinning reserves were adopted to cover the possible forecast deviations in [10, 11], but this modification in spinning reserves is theoretically proved to be inadequate in large deviation situations. Hence, several stochastic unit commitment (UC) models have been proposed, including scenarios-based optimization [12, 13], robust optimization with interval uncertainty [14, 15] and chance-constrained stochastic UC [16], to inherently utilize the different descriptions in wind power forecast uncertainties. All the literatures above are also suitable to involve the stochastic nature of other renewable resources.

After combining low-carbon technique and renewables integration, it is claimed that fossil-fueled plants equipped with flexible CCS devices possess higher ramping rate and lower minimum output, which is favorable for wind generation accommodation in [17, 18]. A UC model for power system with flexible CCPP and wind generation was proposed in [19], and the frequency response was considered in [20]. However, few literatures have discussed the effects on wind power forecast uncertainties, putting the system in unplanned operation status when the wind power deviation is significantly large.

This paper proposes a stochastic UC model considering intensive wind power generation and coal-fueled plants with flexible CCS devices. The economical operation with CO_2 emission cost is set as the optimization target. A linear re-dispatch strategy is introduced to compensate the wind power deviations to cover the uncertainties. Robust optimization theory is thus applied to provide the reliable countermeasures for power system operators to deal with the wind power deviations.

The paper is organized as follows: Section 2 elaborates relevant issues in low-carbon unit commitment (LCUC) model. Section 3 presents the mathematical formulation of the proposed LCUC model. The transformation of LCUC model into a deterministic MILP problem based on linear robust optimization is presented in Section 4. Case studies in New England 39-bus system are illustrated in section 5 and the conclusions are given in section 6.

2 Relevant issues in LCUC

2.1 Characteristic of carbon capture power plant

In this paper, the coal-fueled power plant equipped with post-combustion solvent/sorbent carbon capture system, which is the most commercially available and efficient type of CCS techniques nowadays, is considered [3]. The CCPP can flexibly control the CO_2 capture rate along with its consumption power by venting channel or sorbent/ solvent storage tanks [6].

According to the previous studies, the output power of CCPPs can be written as follows [8]:

$$P_{i,t}^{\mathrm{CCP}} = P_{i,t}^{\mathrm{Coal}} - P_{i,t}^{\mathrm{CCS}} \tag{1}$$

where $P_{i,t}^{\mathrm{CCP}}$ is the total output of carbon capture plant; $P_{i,t}^{\mathrm{Coal}}$ is the output of plant without CCS system.

$P_{i,t}^{\mathrm{CCS}}$ is the power required by CCS devices of CCPP i in time t, which can be expressed as

$$\begin{cases} P_{i,t}^{\mathrm{CCS}} = P_{i\,\mathrm{FIX}}^{\mathrm{CCS}} + \lambda_i^{\mathrm{GE}} \beta_{i,t}^{\mathrm{CCS}} e_i^{\mathrm{G}} P_{i,t}^{\mathrm{Coal}} \\ \beta_{i\min}^{\mathrm{CCS}} \le \beta_{i,t}^{\mathrm{CCS}} \le \beta_{i\max}^{\mathrm{CCS}} \end{cases} \tag{2}$$

where $P_{i\,\mathrm{FIX}}^{\mathrm{CCP}}$ is the fixed power penalty independent from the operation state; λ_i^{GE} is the electric energy consumption to capture 1 ton of CO_2; e_i^{G} is the gross emission of CO_2 when generating 1 MWh of electric energy, and λ_i^{GE} is the adjustable CO_2 capture rate ($\beta_{i,t}^{\mathrm{CCS}}$ and e_i^{G} can be assumed as constants for a specific CCPP).

For simplicity, coal-fueled plant without CCS is not independently modeled in this paper, since it can be seen as a special CCPP when $\beta_{i\min}^{\mathrm{CCS}} = \beta_{i\max}^{\mathrm{CCS}} = 0$ and $P_{i\,\mathrm{FIX}}^{\mathrm{CCS}} = 0$. In this paper, 'coal-fueled plant' only refers to the part of CCPP excludes CCS device.

2.2 Description of wind power forecast error

The stochastic nature of wind power leads to the poor accuracy in short-term spot forecast. Hence probabilistic approaches providing expected wind power values along with quantitative uncertainty description may be better choices.

As mentioned in Section 1, there are roughly three methods to quantify the forecast uncertainty. The most widely used one is the interval description, which gives the bounds of possible wind power under different confidence levels [9].

The wind power $W_{m,t}$ is expressed as

$$\begin{cases} W_{m,t} = W_{m,t}^{\mathrm{F}} + \Delta W_{m,t} \\ \underline{W}_{m,t} \le W_{m,t} \le \overline{W}_{m,t} \end{cases} \tag{3}$$

where $W_{m,t}^{\mathrm{F}}$ is the expected wind output of plant m at time t; $\overline{W}_{m,t}$ is the upper limit; $\underline{W}_{m,t}$ is the lower limit; $\Delta W_{m,t}$ is the power deviation from $W_{m,t}^{\mathrm{F}}$, which is unknown in day-ahead UC planning. Thus, $W_{m,t}$ should be treated as a random variable.

2.3 Wind power curtailment

The possible wind power curtailment is always considered as an economical choice or a measure to control exceeded range of wind power fluctuations. In this paper, the curtailment power $W_{m,t}^{\mathrm{Cur}}$ in the UC model is an uncertain variable defined by a given ratio $\mu_{m,t}^{\mathrm{W}}$ of the available wind power as follows.

$$\begin{cases} W_{m,t}^{\mathrm{Cur}} = \mu_{m,t}^{\mathrm{W}} W_{m,t} \\ 0 \le \mu_{m,t}^{\mathrm{W}} \le 1 \end{cases} \tag{4}$$

2.4 Linear re-dispatch strategy

The deviation of wind power from spot forecast value must be compensated by other power plants to maintain normal frequency. In this paper, a linear re-dispatch strategy is proposed to fulfill this power regulation, and it can be expressed as

$$\begin{cases} \Delta P_{i,m,t}^{\mathrm{Coal}} = K_{i,m,t}^{\mathrm{Coal}} \Delta W_{m,t} \\ \Delta P_{i,m,t}^{\mathrm{CCS}} = K_{i,m,t}^{\mathrm{CCS}} \Delta W_{m,t} \end{cases}$$
$$\sum_{i \in G} \left(\Delta P_{i,m,t}^{\mathrm{Coal}} + \Delta P_{i,m,t}^{\mathrm{CCS}} \right) + \left(1 - \mu_{m,t}^{\mathrm{W}} \right) \Delta W_{m,t} = 0 \tag{5}$$

where $K_{i,m,t}^{\mathrm{Coal}}$ and $K_{i,m,t}^{\mathrm{CCS}}$ are the coefficients with regard to the output adjustment in CCP i to compensate the output deviation of wind plant m; $\Delta P_{i,m,t}^{\mathrm{Coal}}$ and $\Delta P_{i,m,t}^{\mathrm{CCS}}$ are the power adjustment conducted by both the coal-fueled plant and the CCS device; $K_{i,m,t}^{\mathrm{Coal}}$ and $K_{i,m,t}^{\mathrm{CCS}}$ are variables determined by solving the UC problem; G is the set of CCPPs.

Practically, small but fast changing power unbalance may still exist after re-dispatching and it is hard to predict or manually handle. As a result, AGC and primary frequency response will step in, but it is beyond the concern of UC model in this paper.

2.5 UC robustness

A robust UC means a day-ahead commitment plan that can provide feasible regions for real-time dispatching under all possible scenarios of wind power series. In this paper, it is equivalent to a specific unit commitment with the corresponding re-dispatching plan which is suitable for any wind power values within the uncertainty interval.

Usually the wind power is hardly to realize the extreme value at the same time in all the wind plants. Hence, Γ_t^{W} is introduced to restrict the simultaneous deviations of different random variables from the expected values as follows:

$$\underline{W}_{m,t}^{\Gamma} \le W_{m,t} \le \overline{W}_{m,t}^{\Gamma}$$
$$\begin{cases} \underline{W}_{m,t}^{\Gamma} = W_{m,t}^{\mathrm{F}} - \varphi_{m,t} \left(W_{m,t}^{\mathrm{F}} - \underline{W}_{m,t} \right) \\ \overline{W}_{m,t}^{\Gamma} = W_{m,t}^{\mathrm{F}} + \varphi_{m,t} \left(\overline{W}_{m,t} - W_{m,t}^{\mathrm{F}} \right) \\ \sum_{m \in W} \varphi_{m,t} \le \Gamma_t^{\mathrm{W}}, |W| \ge \Gamma_t^{\mathrm{W}} \ge 0 \end{cases} \tag{6}$$

where W is the set of wind plants; $|W|$ is the number of wind plants in the power system; $\varphi_{m,t}$ is the decisive variable controlling the variation range of wind plant output according to Γ_t^{W}. Under such an assumption, the actual limits of wind power $W_{m,t}$ are decisive variables to be optimized, represented by Γ-limits as $\overline{W}_{m,t}^{\Gamma}$ and $\underline{W}_{m,t}^{\Gamma}$.

3 Low-carbon unit commitment model

3.1 Optimization objective

The optimization objective of LCUC is to minimize the total cost for daily fuel consumption and CO_2 emission under expected wind power output.

$$\min \sum_{t}^{T_{\mathrm{UC}}} \left(C_{\mathrm{CO_2}} \sum_{i \in G} E_{i,t}^{\mathrm{CO_2}} + C_{\mathrm{Coal}} \sum_{i \in G} F_{i,t}^{\mathrm{Coal}} + \sum_{i \in G} C_{i,t}^{\mathrm{SU}} + \sum_{i \in G} C_{i,t}^{\mathrm{SD}} \right) \Bigg|_{W_{m,t} = W_{m,t}^{\mathrm{F}}} \tag{7}$$

where $C_{\mathrm{CO_2}}$ is the CO_2 emission price; C_{Coal} is the coal price; $E_{i,t}^{\mathrm{CO_2}}$ is the CO_2 equivalent emission; $F_{i,t}^{\mathrm{Coal}}$ is the coal consumption; $C_{i,t}^{\mathrm{SU}}$ and $C_{i,t}^{\mathrm{SD}}$ are the startup and shut down prices for CCP i at time t.

3.2 Constraints

The following constraints are included in the LCUC model.

1) Power balance

The power balance should always be maintained between generations and load requirements.

$$\sum_{i \in G} \left(P_{i,t}^{\mathrm{Coal}} - P_{i,t}^{\mathrm{CCS}} \right) + \sum_{m \in W} \left(W_{m,t} - W_{m,t}^{\mathrm{Cur}} \right) = \sum_{k \in L} P_{k,t}^{\mathrm{Load}} \tag{8}$$

where $P_{k,t}^{\mathrm{Load}}$ is the power consumption of load k at time t; L is the set of loads.

2) Spinning reserve

The online generators are available to cover load prediction errors as well as possible power shortage induced by forced-tripping of generators.

$$\begin{cases} \sum_{i \in G} \left(\overline{P}_{i,t}^{\mathrm{Coal}} - \underline{P}_{i,t}^{\mathrm{CCS}} \right) + \sum_{m \in W} \left(W_{m,t} - W_{m,t}^{\mathrm{Cur}} \right) \ge \sum_{k \in L} P_{k,t}^{\mathrm{Load}} + \alpha_t^{\mathrm{up}} \\ \sum_{i \in G} \left(\underline{P}_{i,t}^{\mathrm{Coal}} - \overline{P}_{i,t}^{\mathrm{CCS}} \right) + \sum_{m \in W} \left(W_{m,t} - W_{m,t}^{\mathrm{Cur}} \right) \le \sum_{k \in L} P_{k,t}^{\mathrm{Load}} - \alpha_t^{\mathrm{dn}} \end{cases} \tag{9}$$

where $\overline{P}_{i,t}^{\mathrm{Coal}}$ and $\overline{P}_{i,t}^{\mathrm{CCS}}$ are the currently available upper power limits of coal-fueled plant and CCS system, respectively; $\underline{P}_{i,t}^{\mathrm{Coal}}$ and $\underline{P}_{i,t}^{\mathrm{CCS}}$ are the corresponding lower power limits; α_t^{up} and α_t^{dn} are the upward and downward spinning reserve requirements.

3) Coal-fueled plant output range

The power output range of coal-fueled plant is decided by (10)–(12), which correspond to the minimum and maximum technical power limits, online ramping limits and power limits for startup or shut down operations respectively.

$$\begin{cases} \underline{P}_{i,t}^{\text{Coal}} \le P_{i,t}^{\text{Coal}} \le \overline{P}_{i,t}^{\text{Coal}} \\ \overline{P}_{i,t}^{\text{Coal}} \le u_{i,t} P_{i\max}^{\text{Coal}} \\ u_{i,t} P_{i\min}^{\text{Coal}} \le \underline{P}_{i,t}^{\text{Coal}} \end{cases} \tag{10}$$

where binary decisive variable $u_{i,t}$ is the status of CCPP i at time t, CCPP is online when $u_{i,t} = 1$ while CCPP is offline when $u_{i,t} = 0$; $P_{i\max}^{\text{Coal}}$ and $P_{i\min}^{\text{Coal}}$ are the technical maximum and minimum power limits.

$$\begin{cases} \overline{P}_{i,t}^{\text{Coal}} \le P_{i,t-1}^{\text{Coal}} + U_i^{\text{Coal}} + M_i^{\text{Coal}}\left(1-u_{i,t-1}\right) + M_i^{\text{Coal}}\left(1-u_{i,t}\right) \\ \underline{P}_{i,t}^{\text{Coal}} \ge P_{i,t-1}^{\text{Coal}} - D_i^{\text{Coal}} - M_i^{\text{Coal}}\left(1-u_{i,t-1}\right) - M_i^{\text{Coal}}\left(1-u_{i,t}\right) \end{cases} \tag{11}$$

where U_i^{Coal} and D_i^{Coal} are the maximum upward and downward ramping power of coal-fueled plant, respectively. $M_i^{\text{Coal}} = P_{i\max}^{\text{Coal}} + U_{i,t}^{\text{Coal}} + D_{i,t}^{\text{Coal}}$ is a large number required to disable these constraints when the generator is starting up or shutting down.

$$\begin{cases} \overline{P}_{i,t}^{\text{Coal}} \le P_{i\,\text{SU}}^{\text{Coal}} + M_i^{\text{Coal}} u_{i,t-1} \\ \overline{P}_{i,t}^{\text{Coal}} \le P_{i\,\text{SD}}^{\text{Coal}} + M_i^{\text{Coal}} u_{i,t+1} \end{cases} \tag{12}$$

where $P_{i\,\text{SU}}^{\text{Coal}}$ and $P_{i\,\text{SD}}^{\text{Coal}}$ are the maximum power right after startup and before shutting down, respectively.

4) CCS consumption power range

The consumption power range for CCS is identical to those of the coal-fueled plants as

$$\begin{cases} \underline{P}_{i,t}^{\text{CCS}} \le P_{i,t}^{\text{CCS}} \le \overline{P}_{i,t}^{\text{CCS}} \\ \overline{P}_{i,t}^{\text{CCS}} \le u_{i,t} P_{i\,\text{FIX}}^{\text{CCS}} + \lambda_i^{\text{GE}} \beta_{i\max}^{\text{CCS}} e_i^{\text{G}} P_{i,t}^{\text{Coal}} \\ u_{i,t} P_{i\,\text{FIX}}^{\text{CCS}} + \lambda_i^{\text{GE}} \beta_{i\min}^{\text{CCS}} e_i^{\text{G}} P_{i,t}^{\text{Coal}} \le \underline{P}_{i,t}^{\text{CCS}} \end{cases} \tag{13}$$

$$\begin{cases} \overline{P}_{i,t}^{\text{CCS}} \le P_{i,t-1}^{\text{CCS}} + U_i^{\text{CCS}} + M_i^{\text{CCS}}\left(1-u_{i,t-1}\right) + M_i^{\text{CCS}}\left(1-u_{i,t}\right) \\ \underline{P}_{i,t}^{\text{CCS}} \ge P_{i,t-1}^{\text{CCS}} - D_i^{\text{CCS}} - M_i^{\text{CCS}}\left(1-u_{i,t-1}\right) - M_i^{\text{CCS}}\left(1-u_{i,t}\right) \end{cases} \tag{14}$$

$$\begin{cases} \overline{P}_{i,t}^{\text{CCS}} \le P_{i\,\text{SU}}^{\text{CCS}} + M_i u_{i,t-1} \\ \overline{P}_{i,t}^{\text{CCS}} \le P_{i\,\text{SD}}^{\text{CCS}} + M_i u_{i,t+1} \end{cases} \tag{15}$$

where U_i^{CCS} and D_i^{CCS} are the maximum upward and downward power change of CCS, respectively. M_i^{CCS} is a large number just like M_i^{Coal} and $M_i^{\text{CCS}} = P_{i\,\text{FIX}}^{\text{CCS}} + \lambda_i^{\text{GE}} \beta_{i\max}^{\text{CCS}} e_i^{\text{G}} P_{i\max}^{\text{Coal}} + U_{i,t}^{\text{Coal}} + D_{i,t}^{\text{Coal}}$.

5) Minimum up and down time constraint

For coal-fueled plants, it is impossible to restart the generators immediately after shutting down, or vice versa. The status of generators to consider the minimum up and down time constraints is restricted as

$$\begin{cases} u_{i,t} = 1, \ t \le T_{i\,\text{on}}^{\text{For}} \\ u_{i,t} = 0, \ t \le T_{i\,\text{off}}^{\text{For}} \end{cases} \tag{16}$$

$$\begin{aligned} &1 - \left(u_{i,t} - u_{i,t-1}\right) \ge u_{i,k} \quad \forall t > T_{i\,\text{off}}^{\text{For}}, \\ &\quad k = t - T_{i\,\text{UP}} + 1, \ldots, t-1 \end{aligned} \tag{17}$$

$$\begin{aligned} &u_{i,k} \ge u_{i,t-1} - u_{i,t} \quad \forall t > T_{i\,\text{on}}^{\text{For}}, \\ &\quad k = t - T_{i\text{DN}} + 1, \ldots, t-1 \end{aligned} \tag{18}$$

where $T_{i\,\text{on}}^{\text{For}}$ and $T_{i\,\text{off}}^{\text{For}}$ are the time period to compel CCPP i to keep online or offline at the beginning of commitment plan; $T_{i\,\text{UP}}$ and $T_{i\,\text{DN}}$ are the minimum up and down time, respectively.

6) Wind curtailment percentage

The wind curtailment percentage can be expressed as

$$\sum_{t}^{T_{\text{UC}}} W_{m,t}^{\text{Cur}} \le \rho_m^{\text{Wcur}} \sum_{t}^{T_{\text{UC}}} W_{m,t} \tag{19}$$

where ρ_m^{Wcur} is the maximum percentage of daily wind energy curtailment for wind farm m within any possible wind power scenarios.

7) CO_2 emission

The emission of CO_2 constraint is an optional requirement, expressed as

$$\begin{cases} E_{i,t}^{\text{CO}_2} = e_i^{\text{G}} P_{i,t}^{\text{Coal}} - \left(P_{i,t}^{\text{CCS}} - u_{i,t} P_{i\,\text{FIX}}^{\text{CCS}}\right) \Big/ \lambda_i^{\text{GE}} \\ \sum\limits_{t}^{T_{\text{UC}}} \sum\limits_{i \in G} E_{i,t}^{\text{CO}_2} \le E_{\text{CO}_2}^{\max} \end{cases} \tag{20}$$

where $E_{\text{CO}_2}^{\max}$ is the maximum CO_2 emission for a whole day.

8) Transmission capacity

DC power flow model is introduced here to represent the limits of power flow in all transmission lines.

$$\begin{cases} f_h = \sum\limits_{r \in N} B_{rh} \left[\sum\limits_{i \in G(r)} \left(P_{i,t}^{\text{Coal}} - P_{i,t}^{\text{CCS}}\right) + \sum\limits_{m \in W(r)} \left(W_{m,t} - W_{m,t}^{\text{Cur}}\right) - \sum\limits_{k \in L(r)} P_{k,t}^{\text{Load}} \right] \\ -\overline{f}_h \le f_h \le \overline{f}_h \end{cases} \tag{21}$$

where $\overline{f}_h$ is the capacity of transmission line h; B_{rh} is the sensitivity between injection power into bus r and power flow over line h; $G(r)$, $W(r)$ and $L(r)$ are the sets of CCPPs, wind plants and loads connected to bus r.

In summary, the proposed LCUC model consists of the optimization objective (7) and regular constraints (8)–(21) along with key constraints (2)–(6) mentioned above.

4 Linearization and robust counterparts

4.1 Linearization

The original LCUC model has an optimization objective with non-linear cost of CCPP fuel consumption. Hence, the approximate linearization of the CCPP fuel cost by piece-wise functions [21] is performed to apply linear robust optimization theory and to seek for better efficiency when solving the problem.

4.2 Robust counterpart

The linearized LCUC problem still contains lots of random variables introduced by wind power uncertainty, which is impossible to be solved directly. Hence it must be transformed into an equivalent deterministic form by duality theory, commonly called robust counterpart [22, 23].

The robust counterpart of (22) was presented in [23] with a_v as the random coefficients bearing known bounds a_v^{L}, a_v^{U} and expected values $\bar{a}_v$. Decisive variables φ_v and Γ are introduced just as (6) to control the variation range of a_v. It has been proved that (22) with a_v in a restricted variation range as (23) is equivalent to robust counterpart (24), which has no random coefficients any more. z and p_v are dual variables without physical meanings.

$$\forall \sum_v a_v x_v \le b, \quad a_v \in \left[a_v^{\mathrm{L}}, \quad a_v^{\mathrm{U}}\right], \quad E(a_v) = \bar{a}_v \tag{22}$$

$$\begin{cases} \Re(\Gamma) = \bar{a}_v - \varphi_v\left(\bar{a}_v - a_v^{\mathrm{L}}\right) \le a_v \le \bar{a}_v + \varphi_v\left(a_v^{\mathrm{U}} - \bar{a}_v\right) \\ 0 \le \varphi_v \le 1, \sum_v \varphi_v \le \Gamma \end{cases} \tag{23}$$

Since reference [23] gives that $t_v^{\mathrm{F}} = a_v^{\mathrm{U}} - \bar{a}_v$ and $t_v^{\mathrm{F}} = \bar{a}_v - a_v^{\mathrm{L}}$

$$\begin{cases} \sum_v \bar{a}_v x_v + \Gamma z + \sum_v p_v \le b \\ z + p_v \ge \max\left[(a_v^{\mathrm{U}} - \bar{a}_v)x_v, -(\bar{a}_v - a_v^{\mathrm{L}})x_v\right] \quad z \ge 0, p_v \ge 0 \end{cases} \tag{24}$$

$$\begin{cases} W_{m,t} = W_{m,t}^{\mathrm{F}} + \Delta W_{m,t} \\ W_{m,t}^{\mathrm{Cur}} = \mu_{m,t}^{\mathrm{W}} W_{m,t}^{\mathrm{F}} + \mu_{m,t}^{\mathrm{W}} \Delta W_{m,t} \\ P_{i,t}^{\mathrm{Coal}} = P_{i,t}^{\mathrm{F,Coal}} + \sum_{m \in W} K_{i,m,t}^{\mathrm{Coal}} \Delta W_{m,t} \\ P_{i,t}^{\mathrm{CCS}} = P_{i,t}^{\mathrm{F,CCS}} + \sum_{m \in W} K_{i,m,t}^{\mathrm{CCS}} \Delta W_{m,t} \end{cases} \tag{25}$$

Before applying this robust counterpart transformation in the LCUC model, all the random power output must be rewritten as (25).

Then power balance constraint is converted without further transformation as

$$\sum_{i \in G}\left(P_{i,t}^{\mathrm{F,Coal}} - P_{i,t}^{\mathrm{F,CCS}}\right) + \sum_{m \in W}\left(1 - \mu_{m,t}^{\mathrm{W}}\right) W_{m,t}^{\mathrm{F}} = \sum_{k \in L} P_{k,t}^{\mathrm{Load}} \tag{26}$$

However, (9)–(11), (13)–(14), (19) and (21) are still required to be transformed for solution. The upward spinning reserve constraint in (9) is demonstrated as

$$\begin{aligned} &-\sum_{i \in G}\left(\overline{P}_{i,t}^{\mathrm{Coal}} - \underline{P}_{i,t}^{\mathrm{CCS}}\right) - \sum_{m \in W} W_{m,t}^{\mathrm{F}}\left(1 - \mu_{m,t}^{\mathrm{W}}\right) \\ &- \sum_{m \in W} \Delta W_{m,t}^{\mathrm{Cur}}\left(1 - \mu_{m,t}^{\mathrm{W}}\right) \le -\sum_{k \in L} P_{k,t}^{\mathrm{Load}} - \alpha_t^{\mathrm{up}} \end{aligned} \tag{27}$$

Secondly, the controllable variation range of random variables $\Delta W_{m,t}$ are expressed as

$$\begin{cases} -\varphi_{m,t}\left(W_{m,t}^{\mathrm{F}} - \underline{W}_{m,t}\right) \le \Delta W_{m,t} \le \varphi_{m,t}\left(\overline{W}_{m,t} - W_{m,t}^{\mathrm{F}}\right) \\ 0 \le \varphi_{m,t} \le 1, \sum_{m \in W} \varphi_{m,t} \le \Gamma_t^{\mathrm{W}} \end{cases} \tag{28}$$

Finally, robust counterpart according to (22)–(24) can be written as

$$\begin{aligned} &\sum_{i \in G}\left(\overline{P}_{i,t}^{\mathrm{Coal}} - \underline{P}_{i,t}^{\mathrm{CCS}}\right) - \Gamma_t^{W} z_t^{\mathrm{USR}} - \sum_{m \in W} p_{m,t}^{\mathrm{USR}} \ge \sum_{k \in L} P_{k,t}^{\mathrm{Load}} + \alpha_t^{\mathrm{up}} \\ &\begin{cases} z_t^{\mathrm{USR}} + p_{m,t}^{\mathrm{USR}} \ge -\left(1 - \mu_{m,t}^{\mathrm{W}}\right)\left(\overline{W}_{m,t} - W_{m,t}^{\mathrm{F}}\right) \\ z_t^{\mathrm{USR}} + p_{m,t}^{\mathrm{USR}} \ge \left(1 - \mu_{m,t}^{\mathrm{W}}\right)\left(W_{m,t}^{\mathrm{F}} - \underline{W}_{m,t}\right) \\ z_t^{\mathrm{USR}} \ge 0, p_{m,t}^{\mathrm{USR}} \ge 0 \end{cases} \end{aligned} \tag{29}$$

The transformations of other constraints are similar so as to neglect the details in this paper. The LCUC problem is eventually changed into a MILP representation which is ready to be efficiently solved.

5 Case study

The case studies are conducted based on the modified New England 39-bus system. The generator and CCS data are listed in Table 1 and Table 2. In all the cases, three 800 MW wind farms are connected to the bus 30, 32 and 39, respectively. The forecast error for wind power predictions are assumed to be 30% while the curtailment limit ρ_m^{Wcur} for each wind farm is set to be 1%. The branch and base load data are adopted from 'case39' in Matpower 4.1 toolbox [24] for MATLAB. IBM ILOG CPLEX V12.4 is used as the MILP solver.

The load and wind farm output forecasts are given in per unit value in Fig. 1.

For simplicity, loads at different nodes share the same per unit forecast data. Finally, the price of CO_2 emission is 30 \$/tCO_2; the CO_2 emission limit of a whole day is 100000 tCO_2; the spinning reserves α_t^{up} and α_t^{dn} are set as 10% of the total loads and Γ_t^{W} is set to be 3 which leads to the most robust solution which means maximum ranges of wind power variations are considered.

5.1 Validation of LCUC model

Fig. 2 indicates that the available generation range is able to cover the net load variation including the wind power forecast errors and spinning reserves.

The maximum load-carrying rates of all branches are obtained with wind power scenarios generated within the forecast intervals by Monte Carlo simulation. In Fig. 3, the maximum load-carrying rates are normalized by the transmission capacities. It can be noticed that all the branch loads are kept in a safe range.

If all the loads are served by the coal-fueled plants without CCS, then 82097 tons of CO_2 will be produced in a whole day. Even with the wind power assisted, the CO_2 emission will reach at least 70737 tons. However, with the help of CCS, the CO_2 produced can be further cut down to 32449 tons, as demonstrated in Fig. 4.

5.2 Advantages of flexible CCS

The CCS devices can swiftly reduce their power output to provide more available margin for upward spinning reserves, as shown in Fig. 5.

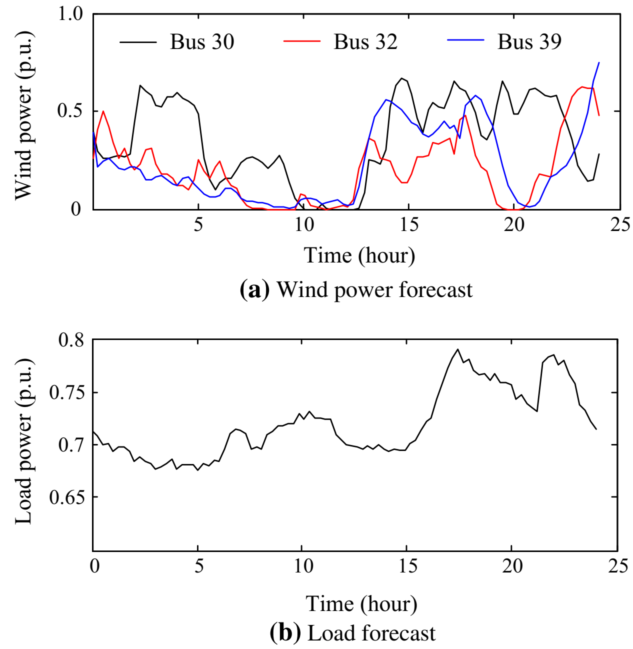

Fig. 1 Load and wind farm output forecasts

Table 1 CCS data in the base case

Bus number	$P^{CCS}_{i\,FIX}$ (MW)	CO_2 capture rate		λ^{GE}_i (MWh/tCO_2)	e^{G}_i (tCO_2/MWh)	15 min ramp range (MW)			
		$\beta^{CCS}_{i\max}$	$\beta^{CCS}_{i\min}$			U^{CCS}_i	D^{CCS}_i	P^{CCS}_{iSU}	P^{CCS}_{iSD}
30	5.2	0.9	0	0.23	0.76	122	122	120	120
31	3.23	0.9	0	0.23	0.76	76	76	75	75
32	3.62	0.9	0	0.23	0.76	85	85	85	85
33	3.26	0.9	0	0.23	0.76	76	76	75	75
39	5.5	0.9	0	0.23	0.76	130	130	130	130

Table 2 Generator data in the base case

Bus number	Technical limits (MW)		15 min ramp range (MW)				Up and down time (hour)		Fuel cost coefficients ($/MWh)			Startup/shut down cost ($)	
	$P^{Coal}_{i\max}$	$P^{Coal}_{i\min}$	U^{Coal}_i	D^{Coal}_i	P^{Coal}_{iSU}	P^{Coal}_{iSD}	$T_{i\,UP}$	$T_{i\,DN}$	a	b	c	A^{SU}_i	A^{SD}_i
30	1040	416.0	156	156	420	420	10.0	9.0	0.0140	20	500	7000	7000
31	646	258.4	120	120	270	270	7.5	6.0	0.0200	20	380	5500	5500
32	725	290.0	130	130	300	300	8.5	7.5	0.0194	20	42	5500	5500
33	652	260.8	110	110	270	270	7.0	7.0	0.0200	20	380	5000	5000
34	508	203.2	80	80	210	210	6.0	6.0	0.0255	20	295	4000	4000
35	687	274.8	105	105	280	280	7.5	7.5	0.0210	20	400	5500	5500
36	580	232.0	90	90	240	240	6.5	6.0	0.0230	20	350	4500	4500
37	564	225.6	90	90	230	230	6.5	6.0	0.0222	20	330	4500	4500
38	865	364.0	150	150	370	370	9.5	9.0	0.0150	20	490	7000	7000
39	1100	440.0	200	200	450	450	10.0	9.0	0.0140	20	500	7000	7000

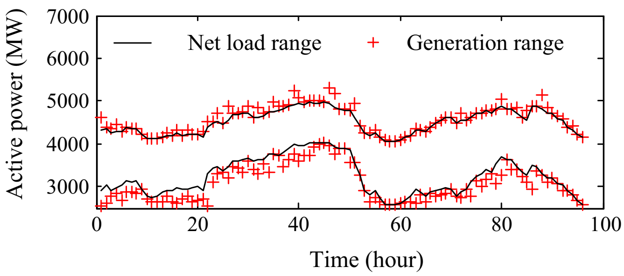

Fig. 2 Power balance between generation and net load

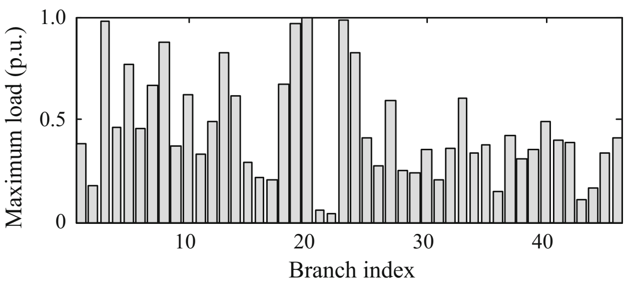

Fig. 3 Maximum load-carrying rate of the branches

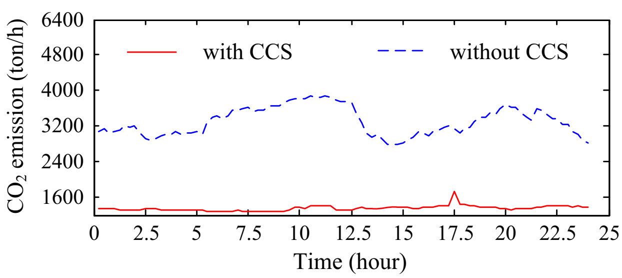

Fig. 4 CO_2 emission reduction

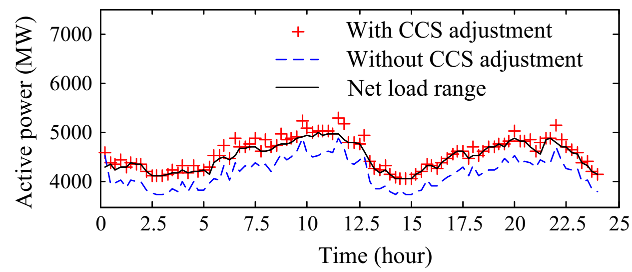

Fig. 5 Upward spinning reserve increased by CCS

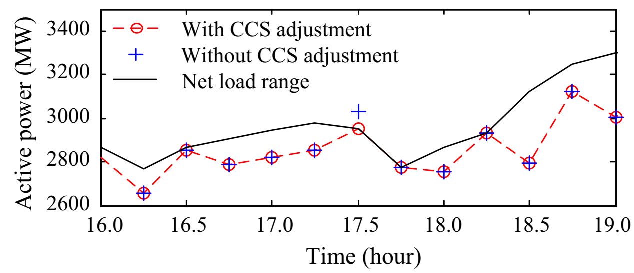

Fig. 6 Downward spinning reserve increased from 16:00 to 19:00

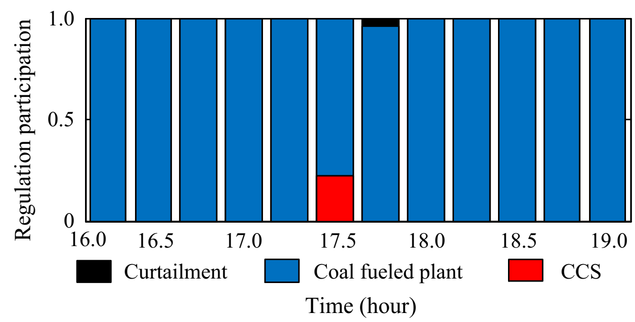

Fig. 7 Wind power regulation participation from 16:00 to 19:00

Furthermore, the CCS devices are allowed to operate at a derating status preparing to increase the power penalty when needed to provide extra downward spinning reserves.

However, the continuous period in derating operation of CCS devices will severely compromise the CO_2 reduction objective. Hence, in the proposed LCUC model, the downward spinning reserve provided from CCS is optimized to be only an emergency precaution, as shown in Fig. 6 and Fig. 7.

5.3 Controlling the robustness

The robustness of the UC plan can be controlled by parameter Γ_t^W aforementioned, which can be chose from 0 (no uncertainty of wind power forecast is considered, namely the least robust) to the wind farm number (the whole wind power uncertainty intervals are considered, namely the most robust). The optimization objectives and constraint violation probabilities with regard to different Γ_t^W are shown in Table 3.

It is shown that Γ_t^W provides a tradeoff between operation security and target optimality. With a smaller range of uncertainty considered, a more optimistic UC plan will be obtained. However the system operation situation may be more tend to risk emergency in the extreme scenarios. The results also indicate that calculation burden will increase when uncertainty of wind power is introduced. When Γ_t^W increases, the time required to solve the LCUC trends to increase.

6 Conclusions

A low-carbon unit commitment model considering flexible CCS and wind power forecast error uncertainties is proposed in this paper. The novel model is finally

Table 3 Tradeoff between operation price and robustness

Γ_t^W	Total cost ($)	CO_2 emission (tons)	Violation probability	Calculation time (s)
3	4081292.5	32449.3	0%	600.29
2.5	4075222.8	32119.8	27.7%	244.42
2.2	4071959.8	31969.4	71.64%	176.91
2.1	4070902.9	31919.3	83.31%	225.55
2	4069851.7	31869.2	92.34%	142.26
1.5	4062824.9	31414.3	100%	149.78
0	4042371.0	29375.8	100%	3.43

converted into a deterministic MILP problem for solution, with a proposed linear re-dispatch strategy and application of linear robust optimization as well. Case studies in New England 39-bus system indicate that the model can efficiently provide reliable and low-carbon UC as well as re-dispatch plan against all realizations of wind power scenarios. Moreover, the robustness of the UC plan can be adjusted to avoid the conservatism which is an attractive feature in practical applications.

Further discussion shows that CCS technique is favorable for intensive wind power accommodation by increasing equivalent ramping rate of generators leading to more adequate spinning reserve. However its adverse effect on constantly changing the CO_2 absorption rate must be carefully considered.

Acknowledgment This work was supported by the National Basic Research Program of China (No. 2012CB215106) and State Grid Corporation of China (No. 52150014006W).

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