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# Day-ahead unit commitment method considering time sequence feature of wind power forecast error

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ABSTRACT

The variable and intermittent nature of large-scale wind power integration makes day-ahead unit commitment (UC) decision-making difficult. This paper establishes a novel and effective UC model with wind power integration by optimizing the utilization of the forecast error and reserve decision. First, considering the temporal feature of the UC model, a time sequence segment-fitting method (TSFM) for the wind power forecast error is presented, in which the non-parametric fitting method is used to address the 'fat-tail' effect of error distribution. Second, according to the probability intervals of the forecast error and characteristic of the reserve, a new reserve decision method is proposed to define three classes of reserve strategies and optimize the capacity for each type of reserve. Third, a UC model with time-varying confidence levels is established by introducing conditional value at risk (CVaR) and chance-constrained programming (CCP), and is linked with the TSFM. This novel model can balance the costs of fuel, various reserves, load shedding risk, and wind curtailment risk, which can improve the economy of the power grid operation. Finally, an improved hybrid particle swarm optimization algorithm with a heuristic searching strategy is applied to solve this multivariate mixed integer non-linear programming problem. The simulation results verify the effectiveness and practicality of the model proposed.

## 1. Introduction

The ever-increasing penetration of large-scale wind power into the power grid has been yielding great economic benefits and challenges to the operation and dispatch of power systems in China. Wind power is regarded as green energy because of its performance in the carbon emission reduction of the power system [1]. However, wind power generation introduces uncertainty into power system operation and decision-making, such as unit commitment (UC), because it is difficult to accurately forecast due to its inherent variability and intermittency [2]. In fact, UC decision integrated wind power has become a significant challenge in power system operation in recent years.

In order to deal with the fluctuation of wind power, the utilization of wind power forecast value, the reserve decision for wind power fluctuation, and the expression of stochastic wind power are generally considered as the most severe problems in UC with wind power integration [3].

To absorb more wind power by the UC decision process, the description of wind power forecast or error data in the UC model should be accurately addressed to reduce the impact of wind power uncertainty [4]. Therefore, probability density functions (PDFs) of the wind power forecast or error values have been recently studied. PDFs such as Normal and Weibull distributions have been generally used to fit the distribution of wind power forecast error [5–7]; however, the 'fat-tailed' effect of forecast error results in unsatisfactory fitting. To improve the fitting accuracy, forecast error has been separated into different bins, fitted in each bin with Beta distribution, and weighted [8]; however, the weighted Beta distribution approaches infinity at the bounds. While, the t location-scale distribution has been used in [9] and a mixed distribution method has been proposed in [10], neither are verified by rigorous test. The non-parametric estimation method has better performance in fitting accuracy compared with above traditional parametric methods, although it has disadvantages associated with calculation sensibility and large sample complexity [11]. Based on the various fitting methods above, forecast and error data have been used in the UC model to improve the accuracy of the UC decision [12–14]. However, the time-varying feature of forecast or error data is not considered, which has been demonstrated in short-term prediction

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## Nomenclature

*Constants*

| | |
|---|---|
| $a$, $b$ and $c$ | coefficients of the unit cost |
| $D_{ri}^t$, $U_{ri}^t$ | ramp-down/ramp-up limit of unit $i$ |
| $f_k(x)$ | probability density at $x$ |
| $h$ | bandwidth of non-parameter fitting method |
| $N_g$ | number of generators that can be conducted |
| $N_W$ | number of wind farms |
| $p_L^t$ | load demand at time $t$ |
| $p_{wj}^t$ | wind power prediction of wind farm $j$ during time period $t$ |
| $p_i^{max}$ | maximum generation limit of unit $i$ |
| $p_i^{min}$ | minimum generation limit of unit $i$ |
| $p(e^f)$ | PDF of the wind power forecast error |
| $R_{s.t}^u$ | up-spinning reserve requirement at time $t$ |
| $R_{s.t}^d$ | down-spinning reserve requirement at time $t$ |
| $r_{ER}^{up}$, $r_{ER}^{down}$ | unit cost of up ER/down ER |
| $r_{TR}^{up}$, $r_{TR}^{down}$ | unit cost of TR-up/TR-down |
| $r_{LL}$, $r_{CW}$ | unit cost of LL/CW |
| $T$ | total scheduling period |
| $T_i^{on}$, $T_i^{off}$ | minimum on/off time intervals of unit $i$ |
| $u_i^t$ | state of unit $i$ during time period $t$ |
| $x_i^t$ | on/off time intervals of unit $i$ before time period $t$ |
| $X_i$ | sample datum |
| $\alpha_k^t$, $\beta_k^t$ | confidence interval parameter during period $t$, k = 1 or 2 |
| $\psi_i$, | hot start cost of unit $i$ |
| $\zeta_i$ | cold start cost of unit $i$ |
| $\tau_i$ | hot start time of unit $i$ |
| $\mu$ | mean of distribution |
| $\sigma$ | standard deviation of distribution |
| $\Delta t$ | time span of the adjacent time |

*Variables*

| | |
|---|---|
| $Cost_{ER}^{down}(\beta_k^t)$ | costs of down extra reserve |
| $Cost_{ER}^{up}(\alpha_k^t)$ | costs of up extra reserve |
| $CVaR_{TR}^{up}$, $CVaR_{TR}^{down}$ | average loss value of upward/downward TR over VaR |
| $CVaR_{LL}$, $CVaR_{CW}$ | average loss value of LL/CW over VaR |
| $Cost_{LLCW}(\alpha_k, \beta_k)$ | risk cost of LLCW |
| $Cost_{TR}(\alpha_k, \beta_k)$ | risk cost of TR |
| $E(\alpha_k^t \beta_k^t)$ | ER cost |
| $F(p_i^t, u_i^t)$ | fuel cost of traditional units |
| $p_i^t$ | generation of unit $i$ during time period $t$ |
| $S(x_i^t, u_i^t)$ | start-up cost of traditional units |
| $u_i^t$ | state of unit $i$ during time period $t$ |
| $V(\alpha_k^t, \beta_k^t)$ | risk cost of TR and LLCW |
| *TR-up/TR-down* | traditional fixed up/down reserve |
| $Z_{\alpha1}/Z_{\alpha2}/Z_{\beta1}/Z_{\beta2}$ | quantiles of confidence levels |
| $\alpha_1/\alpha_2/\beta_1/\beta_2$ | confidence levels of chance constraints |

*Acronyms*

| | |
|---|---|
| CW | curtailment of wind |
| CVaR | conditional value at risk |
| ER | extra reserve |
| LL | loss of load |
| OUFM | overall unsegmented fitting method |
| TSFM | time sequence segment-fitting method |
| TCL | time-varying confidence levels |
| TR | traditional fixed reserve |
| UCL | unique confidence level |
| VaR | value at risk |

studies [15]. The forecast error distribution varies remarkably over time, and can significantly influence the fitting accuracy and UC decisions [14]. Thus, knowing how to capture the time-varying feature of the error is important for effectively improving the utilization of the error data on UC, and needs to be further studied.

Due to the uncertainty of wind power, it is a challenge to choose the type of reserve and economically optimize its capacity in the UC model with integrated wind power, because a small change of reserve capacity or type may initiate a new generator and thus significantly raise operational costs. Besides the traditional power system spinning reserve, various kinds of reserve such as demand response (DR), battery energy storage and electric vehicle (EV) have been widely used to provide reserve for wind power [16–18]. Additionally a hydro-thermal coordination method has been used as an essential reserve in UC decision [19]. Fuzzy energy and reserve co-optimization method has been proposed to schedule the reserve of the power system including uncertain renewable energy [20]. For the optimization of reserve capacity, an optimal model of day-ahead spinning reserve requirement has been proposed while considering the plug-in electric vehicle in [18]. Using a priori analytical method, a formal mathematical framework has been presented to determine the operating reserve requirements [21]. Instead of conventional predicted intervals, an adjustable intervals optimization model has been presented in [22] to schedule the reserve to accommodate the wind power variation and uncertainty. In [23], a two-stage stochastic programming model has been proposed to procure the required load-following reserves from both generation and demand side resources under high wind power penetration. As mentioned above, different types of reserve and optimization of reserve capacity have been discussed. However, in recent studies, coordination of reserve types and optimization of the reserve capacity have not been combined to cope with wind power uncertainty, and the time varying feature of forecast error has not been considered into the reserve decision yet, so these factors need to be further considered.

According to the expression of wind power stochasticity, UC models are generally classified into several categories as follows: scenario-based stochastic programming, chance-constrained programming (CCP), robust optimization, interval programming and risk-based optimization, etc., [24–30]. In [24], scenario-based stochastic programming is used to simulate wind uncertainty, and wind-hydro-thermal coordination problem is established. A risk-based day-ahead unit commitment model considering the risks of load shedding and wind curtailment has been presented to deal with uncertain wind power in [25]. The robust optimization fixes the reserve capacity in the worst-case scenario; therefore, the results are relatively conservative and apt to make the costs high [26]. The 'disable capacity' has been proposed to reveal the risk associated with wind power without providing a method to fix the confidence level [27]. An interval optimization combined with the point estimation method has been proposed to model and solve the UC problem in [28]. A hierarchical UC model using different scheduling strategies in various intervals has been proposed in [29], but the method to divide the two interval has not been mentioned. On the other hand, CCP which sets the constraints with stochastic variables is widely used in UC decision with wind power integration; however, a certain probability limit need to be set ahead of time to ensure the proper utilization of wind power [30]. Considering the time-varying feature of forecast error and requirement of reserve decision, CCP is regarded as suitable method to establish a new UC model in this paper, because the optimal decision can be made in each time period of decision horizon by conveniently flexible confidence level setting.

Consequently, taking the time-varying feature of forecast error and the requirement of reserve decision into account, a more practical UC model with integrated wind power is desirable. Thus, this paper

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