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Rolling Generation Dispatch Based on Ultra-short-term Wind Power Forecast

Qiushi Xu, Changhong Deng
School of Electrical Engineering, Wuhan University, Wuhan, China
Email: xu_qiushi@163.com r

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ABSTRACT

The power systems economic and safety operation considering large-scale wind power penetration are now facing great challenges, which are based on reliable power supply and predictable load demands in the past. A rolling generation dispatch model based on ultra-short-term wind power forecast was proposed. In generation dispatch process, the model rolling corrects not only the conventional units power output but also the power from wind farm, simultaneously. Second order Markov chain model was utilized to modify wind power prediction error state (WPPES) and update forecast results of wind power over the remaining dispatch periods. The prime-dual affine scaling interior point method was used to solve the proposed model that taken into account the constraints of multi-periods power balance, unit output adjustment, up spinning reserve and down spinning reserve.

Keywords: Wind Power Generation; Power System; Rolling Generation Dispatch; Ultra-short-term Forecast; Markov Chain Model; Prime-dual Affine Scaling Interior Point Method

1. Introduction

With the shortage of energy worldwide and the environmental concerns of the public, researchers are working on integrating effectively renewable resources in existing power grids [1]. As the most promising renewable power in technology and economy currently, wind power generation has gradually become a major alternative form. However, wind energy is non stationary and uncontrollable, that result in the uncertainty and intermittence of wind power output and more difficulties to forecast. Therefore, electric power systems economic and safety operation considering large-scale wind power penetration are now facing great challenges, which are based on reliable power supply and predictable load demands in the past.

Advanced power system dispatch technology [2-4] is one of keys for reducing the impacts of the intermittent and uncertainty of wind power output.Economic dispatch (ED) is a method to schedule the generator outputs with the predicted load demands over a certain period of time so as to operate an electric power system most economically[5].The classical ED problem involved only conventional thermal energy power generators. From the recent investigations, security economic dispatch in wind power integrated systems using a conditional risk method was introduced in article[6], a dynamic economic dispatch model based on stochastic programming was introduced in paper[7], optimizing economic/environmental dispatch with wind and thermal units was introduced in paper[8]. These researches basically concentrated in dealing with the scheduling and unit commitment problem day-ahead. However, the characteristic of the predicting accuracy of wind power that decreases with the lapse of time will seriously impair the reasonableness of day-ahead scheduling, and bring about heavy burden for regulation services which are provided by automatic generation control (AGC). It is necessary to consider linking up day-ahead scheduling and AGC on the time scale by more meticulous generation diapatch modes. To achieve this we must incorporate the latest predictive information of wind power into the generation dispatch process.

The objective of this paper is to incorporate ultra-short-term wind power predictive information into the classical economic dispatch problem and propose a rolling generation dispatch mode. In Section II, a method, which is based on the use of discrete time Markov chain models of second order, will be utilized to modify the wind power prediction error state (WPPES) and update forecast results of wind power over the remaining periods. Section III will discuss the system power balance rolling constraints in each dispatch period. Afterward, a rolling generation dispatch model based on ultra-short-term wind power forecast is proposed, which rolling correct not only the conventional units power output but also the power from the wind farm, simultaneously. In Sec-

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tion IV, the prime-dual affine scaling interior point method was used to solve the proposed model. In Section V, the simulation of the ten-unit test system demonstrates the economy and effectiveness of the proposed method. Finally, in Section VI, conclusions are drawn.

2. Wind Power Ultra-short-term Forecast

2.1. Markov Chain Transition Matrices Estimation of WPPES

Non parametric discrete time Markov Chain models have been largely used for generating synthetic wind speed and wind power time series [9-10], providing simulation results that usually offer excellent fit for both the probability density function and the autocorrelation function of the generated wind power time series.

In this paper, in order to avoid the cumulative error form wind forecast to wind power, transition matrices of WPPES are directly estimated using second order Markov model as follows:

$$\Pr\left\{\Delta P_{\mathrm{W}}(t_{h+1})=S_j\left|\Delta P_{\mathrm{W}}(t_h)=S_{i_k},\Delta P_{\mathrm{W}}(t_{h-1})=S_{i_{k-1}},\ldots,\Delta P_{\mathrm{W}}(t_1)=S_{i_1}\right.\right\}$$
$$=\Pr\left\{\Delta P_{\mathrm{W}}(t_{h+1})=S_j\left|\Delta P_{\mathrm{W}}(t_h)=S_{i_k},\Delta P_{\mathrm{W}}(t_{h-1})=S_{i_{k-1}}\right.\right\} \tag{1}$$

for each $j,i_1,i_2,\ldots,i_h\in\{1,\ldots,N\}$, where $\Delta P_{\mathrm{W}}(t_h)$ is the prediction error state over the time interval $[t_{h-1},t_h]$. The state variable is discretized defining a finite set of (representative) values $\{S_1,S_2\ldots,S_N\}$, where N is a calibration parameter, whose setting can refer paper[15]. The minimum and maximum values, S_1 and S_N are set to $-P_{\mathrm{W},n}$ and $P_{\mathrm{W},n}$, respectively, where $P_{\mathrm{W},n}$ is the nominal wind farm power. The remaining values $S_1,S_2,\ \ldots,S_N$ are set to the centers of N-2 classes of equal length defined on the interval $[0,1]$. In a discrete finite Markov process,the probability of a state at any step only depends on the previous state[11].

For N states, the transition matrix, $\mathrm{P}(t_h)$, is an $N\times N\times N$ matrix. The generic element, $p_{kij}(t_h)$, represents the probability that the state of process at t_{h+1} is S_j. An estimate for $p_{kij}(t_h)$ can be obtained as:

$$p_{kij}(t_h)=\frac{n_{kij}(t_h)}{\sum_j n_{kij}(t_h)}\quad\forall k,i,j\quad,\quad\sum_{j=1}^{N}p_{kij}(t_h)=1\quad\forall k,i \tag{2}$$

where $n_{kij}(t_h)$ indicates the number of transitions from state S_k,S_i to state S_j observed in the sequence of WPPES data .

2.2. Forcecasing Procedure in Generation Dispatch

The WPPES time series, $\{\Delta P_{\mathrm{W}}(t_h)\}$, of a wind farm must be s established on the basis of historical wind power data beforehand by

$$\Delta P_{\mathrm{W}}(t_h)=P_{\mathrm{W}}(t_h)-P_{\mathrm{W}\cdot t_h} \tag{3}$$

where

$P_{\mathrm{W}}(t_h)$ average power generated by the wind farm over $[t_{h-1},t_h]$;

$P_{\mathrm{W}\cdot t_h}$ day-ahead forecast power from the wind farm over $[t_{h-1},t_h]$.

Indicating with $\pi(t_h)$ the state probabilities vector at time t_h:

$$\pi(t_h)=[\pi_1(t_h),\pi_2(t_h),\ldots,\pi_N(t_h)] \tag{4}$$

whose generic i-th element, $\pi_i(t_h)$, represents the probability that $\Delta P_{\mathrm{W}}(t_h)$ at the time t_h equals S_i. It is possible to obtain the state probabilities vector at time t_h, as follows:

$$\pi(t_h)=[\pi(t_{h\text{-}1}),\pi(t_{h-2})]\mathrm{P}(t_h) \tag{5}$$

The ultra-short-term wind power forecast procedure can be defined by (5) and $[\pi_0(t_{h\text{-}1}),\pi_0(t_{h-2})]$, the observed state probability vectors at time $t_{h\text{-}1}$ and $t_{h\text{-}2}$, which are computed utilizing only the most recent data collected in the time window. Bye modifying the WPPES over the remaining dispatch periods utilizing the maximum probability state, future wind power can be rolling updated.

3. Rolling Generation Dispatch Model

In general situation, day-ahead dispatch is divided into contiguous and equispaced intervals of length $\Delta t=15\,\mathrm{min}$, totally 96 periods a day. Wind power fast fluctuations, especially minute-to-minute variations, are mostly smoothed by units' inertia and control dead zones [12], so it can be concluded that not all of wind power fluctuations will impair the reasonableness of day-ahead scheduling. In order to link up rolling dispatch and day-ahead scheduling., the time axis is also divided into intervals of length $\Delta t=15\,\mathrm{min}$, updating wind power predictive values and rolling correct units power output and the power from the wind farm every 15 min.

3.1. Power Balance Rolling Constraints

At the initial time in dispatch period h, system power balance rolling constraints are established as:

$$\sum_{i=1}^{N_G}P_{G_i\cdot t}^{h}+P_{W\cdot t}^{h}-P_{L\cdot t}^{latest}=0,$$
$$\text{for each } h=0,1,\ldots,96,\ t=h,h+1,\ldots,96 \tag{6}$$

where

N_G - number of conventional power generators;

h - h -th dispatch period;

$P_{G_i\cdot t}^{h}$ - power from the i-th conventional generator in period t after h times corrected. When h equals to 0, it represents day-ahead schedule power output;

$P_{W\cdot t}^{h}$ power from the wind farm in period t after h times corrected. When h equals to 0, it represents day-ahead forecast power output from the wind farm;

$P_{L\cdot t}^{latest}$ the latest forecast system load in period t.

3.2. Cost Function for Conventional Generator

For the conventional generators, a quadratic cost function will be assumed, which is practical for most of the cases. The total operating cost over the remaining dispatch periods h *to* 96, $f_1(P_{G_i\cdot t}^{h})$, are expressed as:

$$f_1(P_{G_i\cdot t}^{h}) = \sum_{i=1}^{N_G}\sum_{t=h}^{96} C_i(P_{G_i\cdot t}^{h}) \tag{7}$$

where C_i indicates operating cost of i-th conventional generator, which can be represented by

$$C_i(P_{G_i\cdot t}^{h}) = a_i {P_{G_i\cdot t}^{h}}^2 + b_i P_{G_i\cdot t}^{h} + c_i \tag{8}$$

where a_i, b_i and c_i are cost coefficients for the i-th conventional generator, which are found from the input–output curves of the generators and are dependent on the particular type of fuel used [13].

3.3. Abandoned Wind Power Calculate

Based on the ultra-short-term wind power forecast values, abandoned wind power over the remaining dispatch periods can be calculated as follows:

$$f_2(P_{W\cdot t}^{h}) = \sum_{t=h}^{T}({P_{W\cdot t}^{h}}^{*} - P_{W\cdot t}^{h}) \tag{9}$$

where

$f_2(P_{W\cdot t}^{h})$ abandoned wind power over the periods h *to96*;

${P_{W\cdot t}^{h}}^{*}$ ultra-short-term forecast power output from the wind farm in period t.

3.4. Other Constraints

1) Wind farm output limits:

$$0 \le P_{W\cdot t}^{h} \le {P_{W\cdot t}^{h}}^{*},\ \text{for each}\ t = h, h+1, \ldots 96 \tag{10}$$

2) Generator ramp rate limits:

$$\Delta P_{G_i\cdot dn} \times T_{15} \le P_{G_i\cdot t}^{h} - P_{G_i\cdot t-1}^{h} \le \Delta P_{G_i\cdot up} \times T_{15} \tag{11}$$

where $\Delta P_{G_i\cdot up}$ and $\Delta P_{G_i\cdot dn}$ are ramp-up and ramp-down rate limits of i-th generator, respectively. T_{15} = $15\,\text{min}$.

3) Generator power operating limits:

$$P_{G_i \min} \le P_{G_i\cdot t}^{h} \le P_{G_i \max} \tag{12}$$

where $P_{G_i \max}$ and $P_{G_i \min}$ are the minimum and the maximum power outputs of i-th generator, respectively.

4) Regulation deviation limits:

In order to ensure the relevance of day-ahead scheduleing and rolling scheduleing,the maximum regulation deviation for conventional generators are set as:

$$\left|P_{G_i\cdot t}^{h} - P_{G_i\cdot t}^{0}\right| \le \gamma_i \tag{13}$$

where γ_i is the maximum regulation deviation allowable for i-th generators.

5) Up and down spinning reserve constraints:

Integrated large-scale wind power, the system needs additional spinning reserve capacity to reduce the probability of load shedding and release regulation capability of AGC generators.

$$P_{L\cdot t}^{latest} \times L_{\mathrm{u}}\% + {P_{W\cdot t}^{h}}^{*} \times w_{\mathrm{u}}\% \le \sum_{i=1}^{N_G} P_{\mathrm{us}G_i\cdot t}^{h} \tag{14}$$

$$P_{L\cdot t}^{latest} \times L_{\mathrm{d}}\% + {P_{W\cdot t}^{h}}^{*} \times w_{\mathrm{d}}\% \le \sum_{i=1}^{N_G} P_{\mathrm{ds}G_i,t}^{h} \tag{15}$$

$$P_{\mathrm{us}G_i,t}^{h} = \min(P_{G_i \max} - P_{G_i\cdot t}^{h},\ T_{10} \times \Delta P_{G_i\cdot up}) \tag{16}$$

$$P_{\mathrm{ds}G_i,t}^{h} = \min(P_{G_i\cdot t}^{h} - P_{G_i \min},\ T_{10} \times \Delta P_{G_i\cdot dn}) \tag{17}$$

where

$P_{\mathrm{us}G_i,t}^{h}$ up spinning reserve capacity of i-th generator in period t;

$P_{\mathrm{us}G_i,t}^{h}$ down spinning reserve capacity of i-th generator in period t;

T_{10} response time of spinning reserve, $T_{10}=10\,\text{min}$;

$L_{\mathrm{u}}\%$ coefficient of up spinning reserve demand for system load prediction error;

$L_{\mathrm{d}}\%$ coefficient of down spinning reserve demand for system load prediction error;

$w_{\mathrm{u}}\%$ coefficient of up spinning reserve demand for wind power prediction error;

$w_{\mathrm{d}}\%$ coefficient of down spinning reserve demand for wind power prediction error.

3.5. Rolling Generation Dispatch Model

The penalty factor, ω, is incorporate into rolling generation dispatch model for coordinating the contradictory relations between minimizing operating cost of conventional generators and not abandoning wind power .In this paper, ω is set at a value more than equivalent cost for converting per unit of wind power into conventional generator output, taking value $\max(a_i\gamma_i + 2a_i P_{G_i \max} + b_i)$ in the numerical example. Based on (6)-(17) the rolling generation dispatch model can be written as follows:

Minimize

$$F = \omega f_1 + f_2 = \frac{1}{2}\boldsymbol{x}^{\mathrm{T}}\boldsymbol{H}\boldsymbol{x} + \boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} \tag{18}$$

subject to

$$h(\boldsymbol{x}) = \boldsymbol{0} \tag{19}$$

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$$\underline{\boldsymbol{g}} \le g(\boldsymbol{x}) \le \overline{\boldsymbol{g}} \tag{20}$$

where

F total cost over the remaining dispatch periods *h to* 96;

$\boldsymbol{H}$ quadratic coefficient matrix of the objective function;

$\boldsymbol{c}$ coefficient vector of one degree term;

$\boldsymbol{x}$ power output variables from conventional generators and wind farm;

$h(\boldsymbol{x})$ equality constraint function;

$g(\boldsymbol{x})$ inequality constraint function, whose upper and lower limit is $\overline{\boldsymbol{g}}$ and $\underline{\boldsymbol{g}}$, respectively.

4. Prime-dual Affine Scaling Interior Point Method

4.1. Solving Method

The primary problem in this paper, a convex quadratic programming problem due to $\boldsymbol{H}$ is a positive semi-definite matrix, was divided into a series of logarithmic barrier sub-problems, and then prime-dual affine scaling interior point method[14] was utilized to get the optimal solution along the direction of original-Lagrange dual center path through iterations.

First, the linear constraints from (19) to (20) were converted to the following standard forms:

$$\begin{cases} s.t.\ \ h(\boldsymbol{x}) = \boldsymbol{A}_1\boldsymbol{x} - \boldsymbol{b}_1 = \boldsymbol{0} \\ \begin{bmatrix} 1 & \boldsymbol{0} & -\overline{\boldsymbol{g}} \\ -1 & \underline{\boldsymbol{g}} & \boldsymbol{0} \end{bmatrix}\begin{bmatrix} g(\boldsymbol{x}) \\ \boldsymbol{e} \\ \boldsymbol{e} \end{bmatrix} = \boldsymbol{A}_2\boldsymbol{x} - \boldsymbol{b}_2 \le \boldsymbol{0} \end{cases} \tag{21}$$

where $\boldsymbol{A}_1$, $\boldsymbol{A}_2$ represent coefficient matrix of the constraints function in (21), $\boldsymbol{b}_1$, $\boldsymbol{b}_2$ indicate constant term vectors, $\boldsymbol{e}$ is an unit column vector. By introducing slack variables, satisfing $\begin{bmatrix} \boldsymbol{A}_1, \boldsymbol{0} \\ \boldsymbol{A}_2, \boldsymbol{I} \end{bmatrix}\begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{x}_s \end{bmatrix} = \begin{bmatrix} \boldsymbol{b}_1 \\ \boldsymbol{b}_2 \end{bmatrix}$, $\boldsymbol{x}_s(\ge \boldsymbol{0})$, the Lagrange dual problem can be obtained as (22).

$$\begin{cases} \text{Maximize} \quad -\dfrac{1}{2}\boldsymbol{x}^{\mathrm{T}}\boldsymbol{H}\boldsymbol{x} + \boldsymbol{b}^{\mathrm{T}}\boldsymbol{y} \\ s.t.\ \begin{bmatrix} \boldsymbol{H} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} \end{bmatrix}\begin{pmatrix} \boldsymbol{x} \\ \boldsymbol{x}_s \end{pmatrix} + \begin{bmatrix} \boldsymbol{c} \\ \boldsymbol{0} \end{bmatrix} - \boldsymbol{A}^{\mathrm{T}}\boldsymbol{y} = \boldsymbol{z}, \boldsymbol{z} \ge \boldsymbol{0} \end{cases} \tag{22}$$

where $\boldsymbol{y}$, $\boldsymbol{z}$ are Lagrange multiplier vectors of the equality and inequality constraints, respectively. $\boldsymbol{I}$ is an unit matrix, $\boldsymbol{A} = \begin{bmatrix} \boldsymbol{A}_1, \boldsymbol{0} \\ \boldsymbol{A}_2, \boldsymbol{I} \end{bmatrix}, \boldsymbol{b} = \left[\boldsymbol{b}_1^{\mathrm{T}}, \boldsymbol{b}_2^{\mathrm{T}}\right]^{\mathrm{T}}$.

Introducing the barrier parameter, $\mu(>0)$, and making

$$\boldsymbol{x}_t = (\boldsymbol{x}^{\mathrm{T}}, \boldsymbol{x}_s^{\mathrm{T}})^{\mathrm{T}}, \boldsymbol{H}_t = \begin{bmatrix} \boldsymbol{H} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} \end{bmatrix}, \boldsymbol{c}_t = \begin{bmatrix} \boldsymbol{c} \\ \boldsymbol{0} \end{bmatrix},$$

the original-Lagrange dual center path

$$\{\boldsymbol{w}(\mu) = (\boldsymbol{x}_t(\mu), \boldsymbol{y}(\mu), \boldsymbol{z}(\mu))\}$$

meets perturbed Karush-Kuhn-Tucker (KKT) conditions as follows:

$$\begin{cases} \boldsymbol{H}_t\boldsymbol{x}_t + \boldsymbol{c}_t - \boldsymbol{A}^{\mathrm{T}}\boldsymbol{y} = \boldsymbol{z} \\ \boldsymbol{A}\boldsymbol{x}_t - \boldsymbol{b} = \boldsymbol{0}, \quad \boldsymbol{x}_t, \boldsymbol{z} \ge \boldsymbol{0} \\ \boldsymbol{Z}\boldsymbol{X}_t\boldsymbol{e} - \mu\boldsymbol{e} = \boldsymbol{0} \end{cases} \tag{23}$$

where $\boldsymbol{X}_t$=diag$(x_{t1},\ldots,x_{tn})$, $\boldsymbol{Z}$=diag$(z_1,\ldots,z_n)$. When $\mu \to 0$, $\boldsymbol{x}_t(\mu)$ and $\boldsymbol{w}(\mu)$ will converge to the optimal solution of the primary problem and the Lagrange dual problem.

4.2. Algorithm Steps

Step1 Input the original parameters and power output interpolations scheduled in the previous period. Update the latest forecast load demand and ultra-short-term forecast wind power over the remaining periods.

Step2 Give the initial point $\boldsymbol{w}^{(0)} = (\boldsymbol{x}_t^{(0)}, \boldsymbol{y}^{(0)}, \boldsymbol{z}^{(0)})$, satisfing interior conditions.Set admissible error value ε. Set δ=0.1, $p = 0.99, k := 0$.

Step3 Calculate $\boldsymbol{\sigma}$=$\boldsymbol{H}_t\boldsymbol{x}_t^{(k)} + \boldsymbol{c}_t - \boldsymbol{A}^{\mathrm{T}}\boldsymbol{y}^{(k)} - \boldsymbol{z}^{(k)}$,

$\boldsymbol{\rho}$=$\boldsymbol{b} - \boldsymbol{A}\boldsymbol{x}_t^{(k)}$, γ=$\boldsymbol{x}_t^{(k)\mathrm{T}}\boldsymbol{z}^{(k)}$, μ=$\delta\dfrac{\gamma}{n}$.

Step4 Judgment of terminal condition. If the inequalities hold simultaneously, $\|\boldsymbol{\sigma}\|_1 < \varepsilon$, $\|\boldsymbol{\rho}\|_1 < \varepsilon$, $\gamma < \varepsilon$, to end. Otherwise, go to Step5.

Step5 Determine the search direction and step length. By solving the following equation:

$$\begin{bmatrix} \boldsymbol{Z}^{(k)} & \boldsymbol{0} & \boldsymbol{X}_t^{(k)} \\ \boldsymbol{A} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{H}_t & \boldsymbol{A}^{\mathrm{T}} & I \end{bmatrix}\begin{bmatrix} \Delta\boldsymbol{x}_t^{(k)} \\ \Delta\boldsymbol{y}^{(k)} \\ \Delta\boldsymbol{z}^{(k)} \end{bmatrix} = \begin{bmatrix} \boldsymbol{X}_t^{(k)}\boldsymbol{Z}^{(k)}\boldsymbol{e} - \mu\boldsymbol{e} \\ \boldsymbol{0} \\ \boldsymbol{0} \end{bmatrix} \tag{24}$$

obtain solution of the search direction $(\Delta\boldsymbol{x}_t^{(k)}, \Delta\boldsymbol{y}^{(k)}, \Delta\boldsymbol{z}^{(k)})$. Calculate the step length parameter, λ, in this direction.

$$\lambda = \min\left\{ p\left[\max_{i,j}\left(-\frac{\Delta x_{ti}^{(k)}}{x_{ti}^{(k)}}, -\frac{\Delta z_j^{(k)}}{z_j^{(k)}}\right)\right]^{-1}, 1\right\} \tag{25}$$

Step6 Set

$$\boldsymbol{w}^{(k+1)} = (\boldsymbol{x}_t^{(k)} + \lambda\Delta\boldsymbol{x}_t^{(k)}, \boldsymbol{y}^{(k)} + \lambda\Delta\boldsymbol{y}^{(k)}, \boldsymbol{z}^{(k)} + \lambda\Delta\boldsymbol{z}^{(k)}),$$

$$k := k+1.$$

Go to Step3.

5. Test System

The ten-unit test system is used in this paper to demonstrate the performance of the proposed method. The demand of the system was divided into 24 intervalsor. Conventional generator data and the latest forecast load

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data can be found in **Tables 1** and **2**. The test system was integrated with a wind farm, described by operation data of an actual wind farm, including 56 wind turbines of 2.5 MW, totally 140 MW.

Curves of wind power drawn based on day-ahead forecast date, ultra-short-term forecast date obtained through second order Markov model and actual output date one day can be seen in Fig. 1. In general, the trends in curve 1 are much more similar to those in curve 3 then in curve 2. **Figure 1** also shows that scheduleing only according to day-ahead forecast will result in a certain difference, which will impair the reasonableness of conventional generators power output scheduling ,and may cause a waste of wind energy resources.

Table 1. Latest Load forecast data.

Hour	Load (MW)	Hour	Load (MW)	Hour	Load (MW)
1	1096	9	1984	17	1540
2	1170	10	2132	18	1688
3	1318	11	2206	19	1836
4	1466	12	2280	20	2132
5	1540	13	2132	21	1984
6	1688	14	1984	22	1688
7	1762	15	1836	23	1392
8	1836	16	1614	24	1244

Table 2. Conventional generators data.

Unit	$P_{Gi\max}$ (MW)	$P_{Gi\min}$ (MW)	a_i ($/(MW2•h))	b_i ($/(MW•h))	c_i ($/h)	$\Delta P_{G_i,\ up}$ (MW/min)	$\Delta P_{G_i,\ dn}$ (MW/min)
1	470	150	0.043	21.60	958	4.70	-4.70
2	460	135	0.063	21.05	1313	4.60	-4.60
3	340	73	0.039	20.80	604	3.80	-3.80
4	300	60	0.070	23.90	471	3.53	-3.53
5	260	57	0.056	17.87	601	3.70	-3.70
6	243	73	0.079	21.62	480	3.33	-3.33
7	130	20	0.211	16.51	502	2.00	-2.00
8	120	15	0.480	23.23	639	1.20	-1.20
9	80	10	1.091	19.58	455	0.80	-0.80
10	55	55	0.951	22.54	692	0.55	-0.55

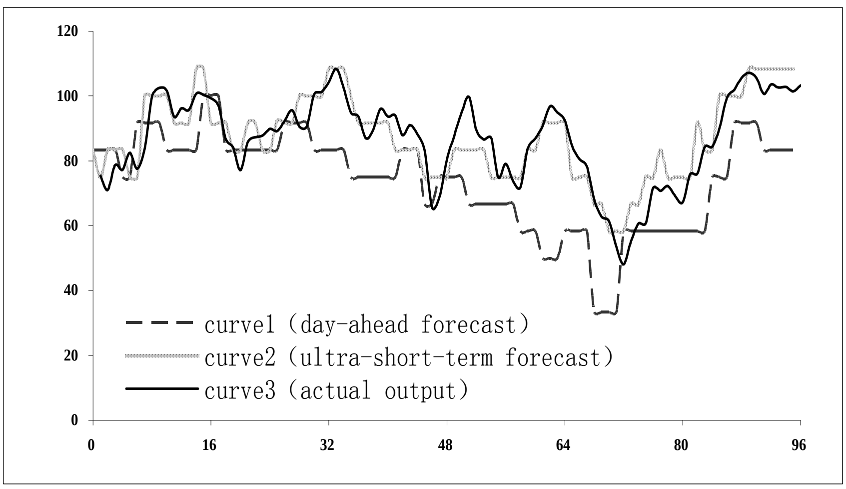

Figure 1. Curves of wind power forecast and actual output of 24-hours.

Table 3. The comparative of objective function values.

Correction	Average abandoned wind power (MW)	Cost for conventional generators ($)	Total cost ($)
before	17.5379	5016455	5076029
after	2.3008	4945263	4953078

Rolling dispatch algorithm is performed at period 30 when day-ahead forecast appears larger deviation shown in **Figure 1**. The hardware environment for testing are 4GB memory and Intel(R)/Core(TM)2/Duo CPU2.80Ghz, programming in MATLAB. In the example, $\gamma_i = 0.1$, $w_u\% = 0.1$, $w_d\% = 0.3$, $L_u\% = 0.05$, $L_d\% = 0.05$, $\omega = 202.8$, $\varepsilon = 0.01$. In this case, the computation time is 1.94s and iteration times are 14, that can meet the needs of online rolling generation dispatch computing. The objective function values before and after correction are shown in **Table 3**, which shows that after rolling correction average abandoned wind power per one period has reduced 15.2371 MW and operating cost for conventional generators has been saved 71192 $. Thus, rolling generation dispatch can not only reduce abandoned wind power, but also make the power system economizing in energy consumption with more wind power accommodated.

6. Conclusions

In this paper, a rolling generation dispatch model based on ultra-short-term wind power forecast, utilizing Markov chain model method, was proposed. In generation dispatch process, the model rolling correct not only the conventional units power output but also the power from wind farm, simultaneously. The simulation results illustrates that the model can effectively promote power system accommodating wind power and optimizing the operation cost. Rolling generation dispatch is necessary in the background of the rapid development of wind power, energy conservation and emission reduction.

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