Economic Dispatch Considering Volatile Wind Power Generation with Lower-Semi-Deviation Risk Measure

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Abstract—**Renewable and low carbon electricity resources have become increasingly popular all over the world. Traditional Economic Dispatch models generally only pursue the minimum of operation cost in a deterministic way, which cannot take the most essential features of these non-dispatchable electricity generations such as WPG (wind power generation). In order to take WPG's uncertainty into account, scenarios are generated where LHS (Latin hypercube sampling) method is adopted, and scenario reduction is applied to reduce the computational burden. Taking advantage of MLASD (mean lower-semi-absolute-deviation) model which can be transformed into simple format and reflects investors' downside loss aversion, the ED model proposed in this paper deals with the trade-off between expectation and risk of the total thermal units' operation cost. Numerical results show that the proposed model can well reflect the essential characteristics of economic dispatch with WPG, and the optimization problem can be solved with fast speed. The proposed model provides a new idea for economic dispatch considering volatile wind power and other kinds of renewable electricity resources.**

Keywords-power system; economic dispatch; wind power generation; MLASD

I. INTRODUCTION

Renewable and low carbon electricity resources have become increasingly popular all over the world. According to many countries' announced plans on renewable energy, the share of electricity from renewable sources will increase step by step and finally maintain or occupy a certain proportion[1, 2]. Among those renewable energy power generation, wind power generation (WPG) is one primary resource and has seen rapid development over the last few years. WPG has been growing fast in China, and the country's wind power installed capacity has seen a rapid increase in recent years and reaches 12GW by 2008[3].

Although WPG has attained a considerable maturity in technology, yet the power output of these generators is still highly depend on randomly-varying weather conditions, which brings about potential hazard when integrate wind power into power systems. The intermittent and volatile nature of WPG may impact power system characteristics such as voltages, frequency, generation adequacy, and so on. Current economic dispatch (ED) methods cannot take the most essential features of these non-dispatchable electricity generations such as WPG. As the pressure to increase renewable generations' penetration is growing rapidly and allowing for the fact that large amount of wind energy has been wasted[4], the limitation of current ED methods has become an issue for grid operators. Existing ED methods generally base on deterministic models and usually neglect the random contingences and the risk that follows. In concern of the limitation above, this paper proposes an ED model based on multi-scenario with risk management considering the violate WPG, which is also applicable to other kinds of renewable electricity resources.

The randomly-varying WPG may increase power system's operation costs with more requirements for spinning reserves and bring about potential risks. In order to get a good accuracy of wind power prediction, many researches focus on developing forecasting tools [5-7]. The 4-years project ANEMOS launched in 2002 and other tools such as Zephyr, Predictor and so on, have improved wind power forecast techniques[8, 9]. Thanks to these tools, wind power is predictable to a limited extent, however, which still cannot achieve enough accuracy for dispatching purposes. It is reasonable to use a set of scenarios and corresponding probabilities as an approximation to model WPG's uncertainty[10-13]. Considering computational burden from a huge number of scenarios, scenario reduction[14] is applied to determine a subset of the initial scenario set and new probabilities are assigned to the preserved scenarios.

Traditional ED models only pursue the minimum of operation cost, while the model proposed here takes both the expectation and risk of operation cost into account. Based on WPG scenarios, the ED model in this paper tries to minimize the risk of operation cost, and requires the average operation cost be less than some level accepted by gird's operator. In dealing with the trade-off between profit and risk, one fundamental issue is how to measure risk. As one kind of lower partial risk measures, lower-semi-absolute-deviation well reflects operators' downside loss aversion[15], and MLASD

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(mean lower-semi-absolute-deviation) model is chosen, which can be reduced into simple format with computational advantage[16-18].

II. WIND POWER SCENARIOS

The wind power forecasting is important in ED considering WPG, however detailed forecast technique is not the focus of this paper. The ED model here assumes load and WPG predictions are available and the hour-by-hour sequences of forecasts are provided as $\hat{d}_t$ and $\hat{w}_t$ respectively, for the successive periods of the dispatch horizon $t = 1,...,T$. Only WPG's uncertainty is considered as volatility of load is much smaller than that of WPG.

The output of WPG depends highly on weather condition and actual wind power may differ from what is forecasted. We assume wind power w_t subjects to a normal distribution $N\left(\mu_t, \sigma_t^2\right)$ with forecasted value $\hat{w}_t$ as its expectation μ_t and a percentage of $\hat{w}_t$ as its standard deviation σ_t, for $t = 1,...,T$. Other statistical distribution can be considered likewise.

Owning to large number of samples required, the well-known Monte Carlo method is often time consuming for simulation, and there have been efforts to reduce the samples required, among which Latin hypercube sampling (LHS) is very popular[19]. In [13], it is demonstrated LHS can approximate the required normal distribution much better than simple Monte Carlo method.

Taking advantage of LHS, scenarios are generated to simulate WPG outputs, and every single scenario is assigned with a probability equals with each other, that is one divided by the total number. In consideration of the computational burden, scenario reduction is adopted to abandon small probability scenarios and integrate close scenarios with new probability assigned, keeping the relative distance between initial scenario set and the reduced one under an acceptable level[14, 20].

III. MLSAD MODEL

The MLSAD model is one kind of mean-lower partial moment models with great importance in the area of portfolio management. Since Markowitz's mean-variance model raised in the 1950s, a great deal of research has been conducted on dealing with the trade-off between high profit and low risk. The mean absolute deviation (MAD) model raised by Konno and Yamazaki in 1991 uses the absolute deviation of the portfolio's rate of return as a measure for risk [17], which can be transformed into a linear programming problem with great computational advantage and it was demonstrated the MAD is consistent with the principle of "maximization of expected utility"[21]. In behavioral finance it is pointed out that investors generally pay more attention to downside loss risk [15], yet neither absolute deviation nor variance considers such investment preference. MLSAD takes investors' downside loss aversion into account, while remains MAD's computational advantage at the same time. MLSAD is applicable for portfolio management and can also be applied to deal with the balance of profit and risk in power system [22].

The MLSAD is presented below. Suppose there are n assets in a portfolio and let the random variable R_i represent the rate of return of the i-th asset, for $i = 1,..,n$. Let r_i be the expectation of R_i and x_i be the proportion in total fund to be invested in the i-th asset. The rate of return of $R(x)$ and its expected value $r(x)$ under the portfolio $x = (x_1,...,x_n)^{\mathrm{T}}$ is given by:

$$R(x) = \sum_{i=1}^{n} R_i x_i$$

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Risk is measured by lower-semi-absolute-deviation:

$$\mathrm{L}_-(x) = \mathrm{E}\left[\left|R(x) - \mathrm{E}\left[R(x)\right]\right|_-\right]$$

where $|v|_- = \max\{0, -v\}$ .The MLASD defines as:

$$\begin{array}{ll} \min & \mathrm{L}_-(x) \\ \text{s.t.} & r(x) = r_1x_1 + ... + r_nx_n \geq r_0, \\ & x_1 + ... + x_n = 1, \\ & l_i \leq x_i \leq u_i, \end{array} \tag{1}$$

where parameter r_0 represents the minimal rate of return required by the investor, scalar l_i is the lower bound of x_i and u_i the upper bound.

Consider a simple semi-absolute-deviation minimization problem below:

$$\begin{array}{ll} \min & |f(y)|_- \\ \text{s.t.} & g(y) \geq 0 \end{array} \tag{2}$$

where $y \in \mathrm{R}$, $f(y)$ and $g(y)$ are scalar functions. Problem (2) is equivalent with such a simple form:

$$\begin{array}{ll} \min & z \\ \text{s.t.} & z + f(y) \geq 0 \\ & z \geq 0 \\ & g(y) \geq 0 \end{array} \tag{3}$$

Apply the idea from (2) to (3), we can transform the MLASD into simple and traditional formats.

IV. ECONOMIC DISPATCH WITH WPG

There are two ED models incorporating with wind power discussed in this paper and only thermal and wind power generation are considered. WPG's volatility is approximated by a set of scenarios, denoted by S (set size: Ns), which could be generated and reduced in section 2. Hence a stochastic problem is transformed into a deterministic one in the solving process. The first model (OCM, Operation Cost Minimization) employs the average operation cost of the Ns scenarios, or the operation cost expectation, as its objective, while the second model (ORM, Operation Risk Minimization) takes advantage of MLASD and tries to minimize operation risk measured by lower-semi-absolute-deviation, requiring the operation cost expectation not more than M_0, an acceptable level appointed by gird's operator. In practice, grid's operator can use the optimization result from MOC model as a reference for deciding M_0.

A. Operation Cost Minimization

The OCM-ED tries to allocate power output among thermal and wind plants so as to minimize the operation cost expectation, subject to constraints that ensure security.

As wind energy is renewable and producing wind power almost costs nothing once the wind farm is built up, wind power output should be adopted fully and there is no account for wind power in the total operation cost.

The objective is:

$$\min \quad M_{\mathrm{E}} = \sum_{s=1}^{Ns} p_s M_s \tag{4}$$

where M_s is the total operation cost in scenario s ($s \in S$), and p_s the probability this scenario takes place. Besides,

$$M_s = \sum_{g=1}^{Ng} \sum_{t=1}^{Nt} C_g\left(P_g^s(t)\right) \tag{5}$$

$$C_g\left(P_g^s(t)\right) = a_g + b_g P_g^s(t) + c_g P_g^s(t)^2 \tag{6}$$

where $P_g^s(t)$ represents the power output of thermal unit g to be dispatched at period t in scenario s, for $g = 1,...,Ng$, $t = 1,...,Nt$, Ng is the number of thermal units and Nt the number of periods in dispatch horizon; C_g is the production cost function of thermal unit g, which is generally approximated by a quadratic function as (6), and a_g, b_g, c_g are the corresponding coefficients.

The model subjects to the following constraints:

1) *The Power Balance Constraint:*

$$\sum_{g=1}^{Ng} P_g^s(t) + \sum_{w=1}^{Nw} P_w^s(t) = D(t) \tag{7}$$

where $D(t)$ is the total power demand at period t; $P_w^s(t)$ is the power output of wind power unit w at period t in scenario s; Nw is the total number of wind power units. Transmission power loss is neglected in this paper.

2) *The Units Operating Constraint:*

$$P_g^{\min} \le P_g^s(t) \le P_g^{\max} \tag{8}$$

$$P_g^s(t) - P_g^s(t-1) \le R_g^{\mathrm{U}} \tag{9}$$

$$P_g^s(t-1) - P_g^s(t) \le R_g^{\mathrm{D}} \tag{10}$$

where $P_g^{\min}$ and $P_g^{\max}$ are the minimum and maximum power outputs of thermal unit g ; R_g^{U} and R_g^{D} are its up-ramp and down-ramp limits.

3) *The Spinning Reserve Constraint:*

$$\sum_{g=1}^{Ng} P_g^{\max} \ge D(t) + R(t) \tag{11}$$

where $R(t)$ is the spinning reserve requirement in period t.

4) *The Adjustment Constraint:*

$$-\Delta_g^{\mathrm{D}} \le P_g^s(t) - P_g(t) \le \Delta_g^{\mathrm{U}} \tag{12}$$

where $P_g^s(t) - P_g(t)$ reflects the variation between what is dispatched at real time in scenario s and what is scheduled day-ahead; Δ_g^{D} and Δ_g^{U} are the maximum active power downside and upside adjustments of unit g. Constraint (12) assures wind power fluctuation can be made up by thermal units.

Formulas (4) - (12) form the OCM-ED model.

B. Operation Risk Minimization

The objective function of ORM-ED is:

$$\begin{aligned} \min \quad Risk &= \sum_{s=1}^{Ns} p_s \left|M_{\mathrm{E}} - M_s\right|_- \\ &= \sum_{s=1}^{Ns} p_s \left|\sum_{s=1}^{Ns} p_s M_s - M_s\right|_- \end{aligned} \tag{13}$$

Compared with the OCM-ED described above, ORM-ED requires another constraint that follows.

5) *The Mean Operation Cost Constraint:*

$$M_{\mathrm{E}} = \sum_{s=1}^{Ns} p_s M_s \le M_0 \tag{14}$$

Formulas (5) - (14) form the ORM-ED model. Making use of the idea from (2) to (3), it could be transformed into simple format with computation advantage.

V. NUMERICAL RESULTS

A system with 10 thermal units is used for numerical tests and analyses of the proposed models. Table 1 provides the thermal units data. As transmission constraint is not considered, the wind power units can be represented by a single unit, whose wind power forecast $P_{\mathrm{W}}^{\mathrm{f}}$ is provided in Table 2, where the load demand is also listed in. The ED models base on an hourly description of power generation and demand, and the dispatch horizon is 24 hours. We assume the spinning reserve requirement be 5% of the load demand and all thermal units' up/down-ramp limits be 180 MW/h, $\Delta_g^{\mathrm{D}} / \Delta_g^{\mathrm{U}}$ be 10 minutes ramping of unit g, that is 1/6 of its corresponding ramping.

TABLE I. THERMAL UNITS' DATA

Unit	P_g^{max} **(MW)**	P_g^{max} **(MW)**	a **($/h)**	b **($/MWh)**	c **($/MW²h)**
1	405	80	1000	16.19	0.00048
2	405	80	970	17.26	0.00031
3	130	20	700	16.60	0.00200
4	130	20	680	16.50	0.00211
5	162	25	450	19.70	0.00398
6	80	20	370	22.26	0.00712
7	85	25	480	27.74	0.00079
8	55	10	660	25.92	0.00413
9	55	10	665	27.27	0.000222
10	55	10	670	27.79	0.00173

TABLE II. HOURLY LOAD AND WIND POWER FORECAST

Hour	**Load/MW**	P_w^f **/MW**	**Hour**	**Load/MW**	P_w^f **/MW**
1	700	190	13	1 400	390
2	750	300	14	1 300	340
3	850	330	15	1 200	320
4	950	360	16	1 050	120
5	1 000	350	17	1 000	10
6	1 100	370	18	1 100	40
7	1 150	440	19	1 200	50
8	1 200	460	20	1 400	20
9	1 300	350	21	1 300	5
10	1 400	250	22	1 100	250
11	1 450	420	23	900	350
12	1 500	380	24	800	240

As practical experiences show WPG forecast's error increases with forecast horizon, we assume in this paper that the forecast standard deviation is $\sigma/2$ in the first 4 hours and σ in the next 20 hours, where σ is chosen as 0.05, 0.1 and 0.2. According to Section 2 and Table 2, 10000 scenarios are generated for each hourly WPG and a 10-size set is remained after scenario reduction (Fig.1).

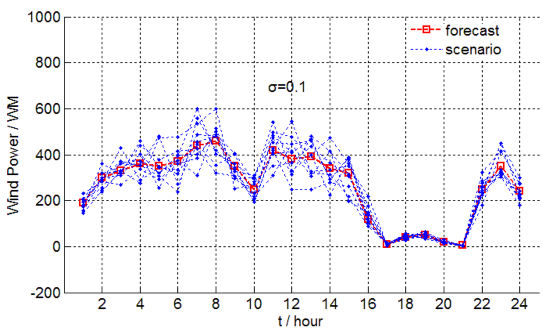

Figure 1. Wind power forecast and remained scenarios at σ =0.1

The two models above are implemented in MATLAB on a PC with Intel Core 2 Duo CPU T7500 and 1.0GB RAM memory. The optimization is solved through Interior-Point method provided by MATLAB. Numerical results show that the models reflect essential features of ED incorporating with WPG and optimization can be solved with fast speed.

1) Operation Cost Minimization

The OCM-ED optimization results for different forecast errors are listed in Table 3, which reveals that operation cost rises as forecast error increases.

TABLE III. OCM-ED RESULTS WITH DIFFERENT FORECAST ERRORS

σ	**Operation Cost Minization ($)**	**Elapsed Time (ms) / Iterations**
0.05	527029	15.31 / 29
0.1	527253	16.81 / 33
0.2	527724	16.18 / 32

2) Operation Risk Minimization

The ORM-ED optimization results are listed in Table 4, which shows the operation cost risk increases with wind power forecast error. Besides, Table 4 demonstrates the general concept that the higher the acceptable level (M_0), the smaller the operation cost risk. Fig. 2 provides the relationship between operation risk and acceptable level (M_0) in σ =0.1 scenario set.

TABLE IV. ORM-ED RESULTS WITH DIFFERENT FORECAST ERRORS AND ACCEPTABLE LEVELS

σ	M_0 **($)**	**Operation Risk Minization ($)**	**Elapsed Time (ms) / Iterations**
0.05	528000	700.4	20.19 / 34
	529000	277.3	23.51 / 37
	530000	99 *	12.81 / 22
0.1	528000	1086.4	22.09 / 38
	529000	741.9	20.04 / 36
	530000	436.4	22.10 / 40
0.2	528000	2759.9	19.76 / 34
	529000	2273.7	23.06 / 35
	530000	1805.3	23.81 / 37

* THE ALGORITHM TERMINATES ONCE THE objective VALUE IS LESS THAN 100 $.

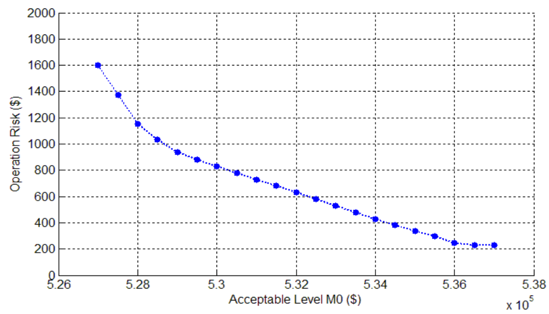

Figure 2. Relationship between operation risk and M0

3) Comparison

The comparison between these two models' dispatch results in the σ =0.1 scenario set is given below. Based on the minimization 527253$ from OCM-ED, the acceptable level M_0 in ORM-ED is appointed as 528000$. Table 5 compares the operation cost in each scenario, and Table 6 compares the operation cost risk measured by lower semi-deviation.

TABLE V. OPERATION COST COMPARISON

scenario	probability	Operation Cost in OCM-ED ($)	Operation Cost in ORM-ED ($)
1	0.2200	527941	526361
2	0.1030	524598	529581
3	0.1020	521656	527997
4	0.0910	529159	532193
5	0.1000	538378	523139
6	0.0830	528368	527999
7	0.0870	526203	525897
8	0.0720	523184	530549
9	0.0790	518323	532534
10	0.0630	525489	526518
average	-	526738	527999
standard deviation	-	5094	2785

TABLE VI. OPERATION RISK COMPARISON

scenario	probability	Operation Risk in OCM-ED ($)	Operation Risk in ORM-ED ($)
1	0.2200	1204	0
2	0.1030	0	1582
3	0.1020	0	0
4	0.0910	2422	4195
5	0.1000	11641	0
6	0.0830	1631	0
7	0.0870	0	0
8	0.0720	0	2551
9	0.0790	0	4535
10	0.0630	0	0
average	-	1785	1086

From the details above, we can draw the conclusion that ORM-ED brings about dispatch instructions with smaller operation risk and guarantees the expectation under an acceptable level.

VI. CONCLUSION

The ORM-ED model proposed in this paper takes WPG's uncertainty into account and makes use of the MLASD model which reflects investors' downside loss aversion and can be transformed into simple format. Numerical results show the proposed model can well reflect the essential characteristics of ED with WPG and is good at dealing with the trade-off between operation cost's expectation and risk, and the optimization problem can be solved with fast speed. The proposed model provides a new idea for economic dispatch considering volatile wind power and other kinds of renewable electricity resources.

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