J. Basic. Appl. Sci. Res., 2(4)3316-3322, 2012
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ISSN 2090-4304
Journal of Basic and Applied Scientific Research
www.textroad.com

Impact of Wind Uncertainties on Generation Dispatch and Unit Commitment

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ABSTRACT

Integration of wind power generation creates new concerns in a power system. Unlike conventional power generation sources, wind power generators supply alternative power due to uncertainty in wind velocity. The impact of wind power forecasting on unit commitment and dispatch is investigated in this paper. The stochastic manner in uncertainty of these parameters has been simulated by creating scenarios that can be solved by deterministic methods. Mixed integer nonlinear programming (MINLP) is used for solving deterministic unit commitment problems with GAMS software. We present two unit commitment methods to consider the variability and alternative of wind power. The uncertainty in wind power forecasting is captured by a number of scenarios in the stochastic unit commitment approach, while a point forecast of wind power output is used in the deterministic alternative. The quality of wind power forecasting has a great impact on unit commitment and dispatch. The stochastic method shows its value in terms of relatively lower dispatch cost. However, the dispatch results are also sensitive to the level of reserve requirement. Our results so far indicate that a deterministic method combined with an increased reserve requirement can produce results that are comparable to the stochastic case. The proposed approach is applied to an 11-unit test system (including 10 conventional units and 1 wind farms. Then, impact of power of wind and location of wind farm on LMP of buses is considered.
KEYWORDS: Unit commitment, generation dispatch, wind turbine uncertainty, stochastic programming.

I. INTRODUCTION

Wind power generation is becoming more popular while the large-scale wind farm is the main stream one. It has potential benefits in cutting the consumption of irreplaceable fuel reserves and reducing the pollutant [1-3] when the demand for electricity has been steadily growing due to the industrial developments and the growth of the economy in most parts of the world. The perpose of Economic Dispatch (ED) is schedule the power generation such that total operational cost is minimized [4]. If a wind plant's output could be perfectly forecasted for several days in advance, it would help schedulers to determine which units should be committed. In the absence of a perfect forecast, the unit commitment (UC) decision must be made under uncertainty. Consequently, the decision may contain a unit to be committed when it is not necessary, and sometimes may not contain a unit for commission while it is necessary. The researcher mentions manners to solve this uncertainty [5-6]. One of these methods is stochastic programming.

In this work, the possible future outcomes of demand were represented by a scenario tree. Since it was impossible to use all of these possible scenarios, we tested their method using 400 scenarios [7].

A numerical application example based on a typical IEEE test power system is used to demonstrate the correctness and effectiveness of the proposed optimization method.

II. Wind farm outputs calculation

The stochastic variation of wind farms outputs root mainly in fluctuation of the wind speeds and directions. If all wind speeds and directions of wind turbines in one wind farm are assumed as same, the wind farm can be simulated by an equal wind turbine.

their probabilities between 0 and 25m/s are considerable; most of the average annual wind

speeds subject to the Weibull distribution[8]. If it is studied in short time periods, the wind speed v can also be assumed to subject to the normal distribution $\phi(v)$, as in (1).

$$\varphi(V)=\frac{1}{\sigma\sqrt{2\pi}}\exp[-\frac{(v-\mu)^2}{2\sigma^2}] \qquad (1)$$

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where μ is the average wind speed; σ is the variance.
The relationship between the wind turbine output is P as in (2).

$$P_w = \begin{cases} 0 & v \le v_{CI} \text{ or } v \ge v_{CO} \\ \frac{P_R}{v_R^3 - v_{CI}^3} v^3 - \frac{v_{CI}^3}{v_R^3 - v_{CI}^3} P_R & v_{CI} \le v \le v_R \\ P_R & v \ge v_R \end{cases} \qquad (2)$$

Where P_R is the rated output of the wind turbine; v is the wind; V_{cr} is the cut-in wind speed; V_R is the cut-out wind speed; v is the rated wind speed.

III. Unit Commitment and Dispatch Model

Unit commitment and dispatch is modeled using mixed-integer stochastic programming model. The model assumes that generators have a three-part cost structure, no load, and startup costs, and includes standard system and generator constraints. In order to give the model formulation, we first define the following decision variables and indices:

$p_{i,t,\sigma}$: generation provided by generator *i* in period *t* under scenario σ ,
$s_{pi,t,\sigma}$: spinning reserves provided by generator *i* in period *t* under scenario σ ,
$u_{i,t,\sigma}$: binary variables indicating if unit *i* is online in period *t* under scenario σ ,
$s_{i,t,\sigma}$: binary variables indicating if unit *i* is started-up in period *t* under scenario σ ,
$h_{i,t,\sigma}$: binary variables indicating if unit *i* is shutdown in period *t* under scenario σ ,
$g_{w,t,\sigma}$: wind generation provided by wind generator *w* in period *t* under scenario σ , and
$l_{t,\sigma}$: load served in time period *t* under scenario σ .
We also define the following decision parameters:
t: time index,
σ : scenario index,
i: generator index,
w: wind generator index,
π_σ : probability of scenario σ ,
$\{\sigma\}t$: set of scenarios that are indistinguishable fromσ at time *t*,
ci: generator *i*'s variable cost,
Ni: generator *i*'s no-load cost,
SUi: generator *i*'s startup cost,
K_i^- : generator *i*'s minimum operating point,
K_i^+ : generator *i*'s maximum operating point,
R_i^-: generator *i*'s rampdown limit,
R_i^+: generator *i*'s rampup limit,
SPi: generator *i*'s spinning reserve capacity,
$\tau^- i$: generator *i*'s minimum down-time,
τ_i^+ : generator *i*'s minimum up-time,
$\omega_{w,t,\sigma}$: generation available from wind generator *w* in period *t* under scenario σ ,
η_s: spinning reserve requirement (as a fraction of load),
RESW: spinning reserve requirement (as a fraction of power of wind under uncertainty),
The objective function of the model is:
$Min\ \sum\pi_\sigma\ [ci(q_{i,t,\sigma}) + N_{iui,t,\sigma} + SU_{isi,t,\sigma}]$

This objective function is maximized subject to the following constraints:

$$l_{t,\delta} = \sum_i g_{t,w,\delta} + \sum_i p_{i,t,\delta} \qquad (3)$$

$$\sum_i sp_{i,t,\delta} \geq \eta^s l_{t,\delta} + RESWg_{w,t,\delta} \tag{4}$$

$$K_i^- u_{i,t,\delta} \leq p_{i,t,\delta} \tag{5}$$

$$p_{i,t,\delta} + sp_{i,t,\delta} \leq K_i^{\ +} u_{i,t,\delta} \tag{6}$$

$$0 \leq sp_{i,t,\delta} \leq \overline{sp}_i u_{i,t,\delta} \tag{7}$$

$$R_i^- \leq p_{i,t,\delta} - p_{i,t,\delta} \tag{8}$$

$$p_{i,t,\delta} - p_{i,t-1.\delta} + sp_{i,t,\delta} \leq R^+_{\ i} \tag{9}$$

$$\sum_{y=t-\tau_i^+} s_{i,y,\delta} \leq u_{i,t,\delta} \tag{10}$$

$$\sum_{y=t-\tau_i^-} h_{i,y,\delta} \leq 1 - u_{i,t,\delta} \tag{11}$$

$$\mathrm{s}_{i,t,s} \ -\mathrm{h}_{i,t,s} = \mathrm{u}_{i,t,s} \ -\mathrm{u}_{i,t-1,s} \tag{12}$$

$$0 \leq \mathrm{g}_{w,t,s} \leq \omega_{w,t,\delta} \tag{13}$$

$$\mathrm{u}_{i,t,s} \ , \mathrm{s}_{i,t,s} \ ,\mathrm{h}_{i,t,s} \ \in \ \{0,1\} \tag{14}$$

Constraints (3) are load-balance limitation, which ensure that the demand isserved in each period. Constraints (4) imposes the spinning requirements. Constraints (5) through (6) ensure that each generator operates between its minimum and maximum limitation, and that it would not violate the upper-bound on its output. Constraint (7) enforces each generator's ancillary service qualifications. Constraints (8) and (9) enforce each generator's ramping limits. Constraints (10) and (11) impose each generator' minimum up- and down-times when they are started up and shutdown. Constraints (12) define the startup and shutdown variables in terms of the online variables. Constraints (13) limit each wind generator's production based on wind availability under each scenario. Constraint (14) imposes non-negativity and integrality limitation.

IV. Model of uncertainty

In the case study we use a hypothetical power system to simulate the impact of using different wind power forecasts and operating reserve policies for the day-ahead unit commitment. In this paper, we consider 400 scenarios for one day. In this method, at first all of the scenarios have the same probability. We use reduction scenario algorithm for simplify this problem, such that the scenarios that have the same, we consider one scenario and the probability

this scenario is summation of other scenarios. Let us denote the forecasted wind power as a series:

$p^{(m)} = \{ p1^{(m)}, \ldots, pT^{(m)}\}$ (15)

for time horizon t = 1, … , T in scenario m = 1, … , M. This is also a point in a space of dimension T. The forecasted wind power scenarios $p^{(m)}$ are normalized with respect to the installed power of the wind farm (or generator) in order to obtain the vectors $x^{(m)}$, whose components lie in the range [0, 1]. Different metrics can be used to define the distance between two scenarios $x^{(i)}$ and $x^{(j)}$. For the work presented in this paper, the maximum deviation has been used:

$d_{max}(x^{(i)} , x^{(j)}) = \max \|X_t^{(i)}-X_t^{(j)}\|,$ $t=1,\ldots,T$ (16)

If $d_{max} (X^{(i)} , X^{(j)}) < \epsilon$, we can say that $X^{(i)}$, $X^{(j)}$ are the same. After scenario reduction we have 13 scenarios with variant probability. Figure (1) shows wind speed in one day and figure (2) shows power of wind that get from scenario reduction algorithm.

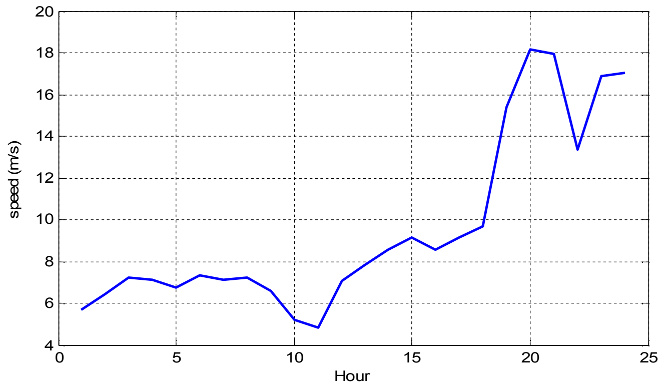

Figure (1): wind speed in one day (m/s)

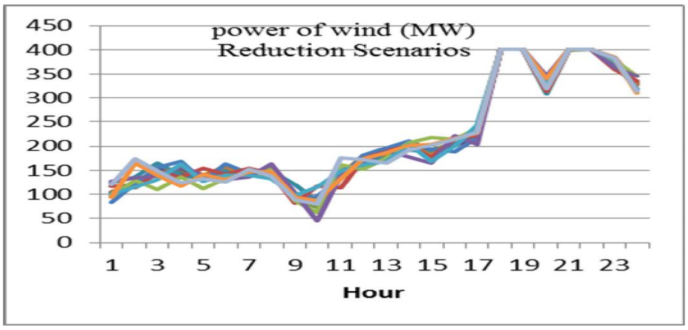

Figure (2): output power of wind farm (MW)

V. STUDY CASE

The hourly profile of the loads is taken from historical data from the state of Illinois for the month of January. However, the load level is scaled down to match the configuration of the generation capacity in the test power system. The total installed capacity is assumed to be 400 MW. The load is shown in Fig. 3. An example of a day-ahead wind power forecast and realized wind generation is shown in Fig. 2. The accuracy of the wind power forecast varies from day to day. The characteristics of the thermal power plants are based on the case studies presented in [9] and [10]. The production cost increases from unit 1 to unit 10.

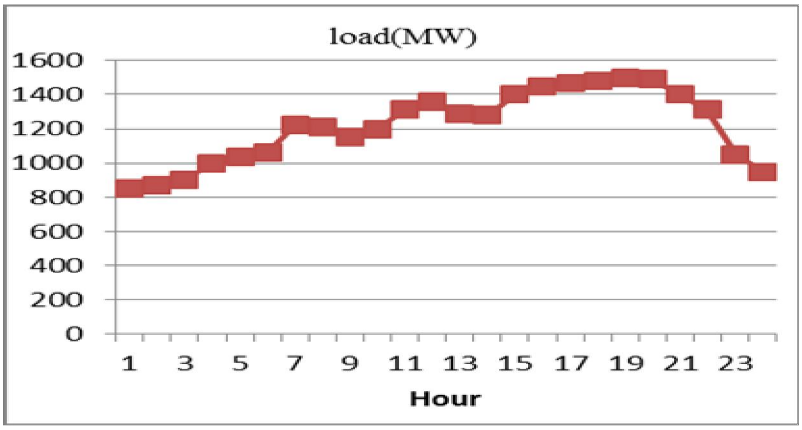

Figure (3): load of system (MW)

VI. Simulation 1

We first present the dispatch results for a selected day. Fig. 4 shows the number of units on-line in cases deterministic and stochastic and average of scenarios. These three cases are chosen since they are relevant candidates for how system operators may incorporate wind power forecast into their UC. In practice, a wind power point forecast is available in most areas with high penetration of wind, and the stochastic unit commitment approach has been shown to be an effective method to accommodate wind uncertainty in system operation. In the figure, we can see the number of on-line units in stochastic programming and deterministic and average of scenarios. Because the stochastic approach considers multiple scenarios in some hours more units are on. A similar effect is obtained with the deterministic approach in reserve requirement. In all cases the amount of available reserve is higher than reserve requirement in the real-time dispatch. Fig.5. shows effect of wind uncertainty on reserve requirement.

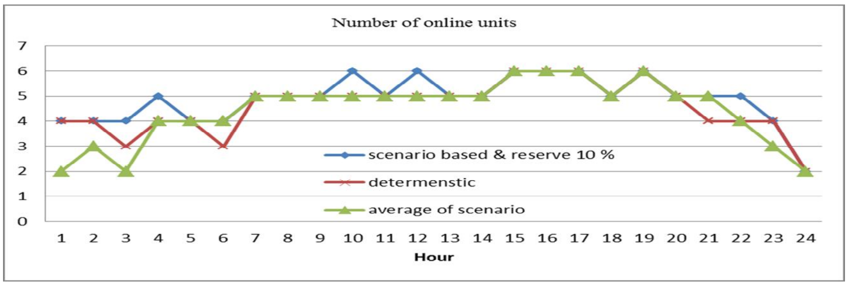

Figure (4): number of units online.

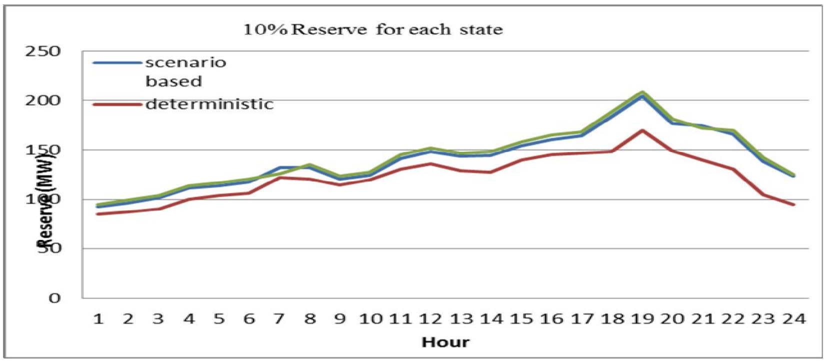

Fig (5): Available operating reserves.

Fig.6. shows operation cost of system. As we seen the total cost in stochastic programming is more than deterministic. Because of uncertainty that output power of wind impose to the system.

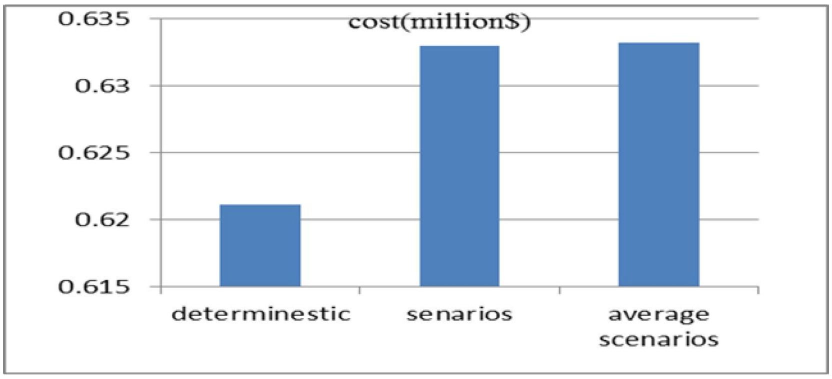

Fig (6): operating costs

It is assumed here that there are different installed wind farm capacities on the system. In this condition we compare the impact of the wind power generation on UC. In this case, the total generation and reserve targets must be met by conventional generation.Fig.7. shows reserve of requirement in one day test system with respect to different wind capacities. As seen in this figure, the reserve requirement UC problem increased while the wind power capacity is increased. Also, the effect of RESW parameter which is selected to model the uncertainty in wind power prediction error of UC problem is shown in Fig. 8. The total reserve power UC problem is increase when the RESW is increased because the reserve requirement must be decreased.

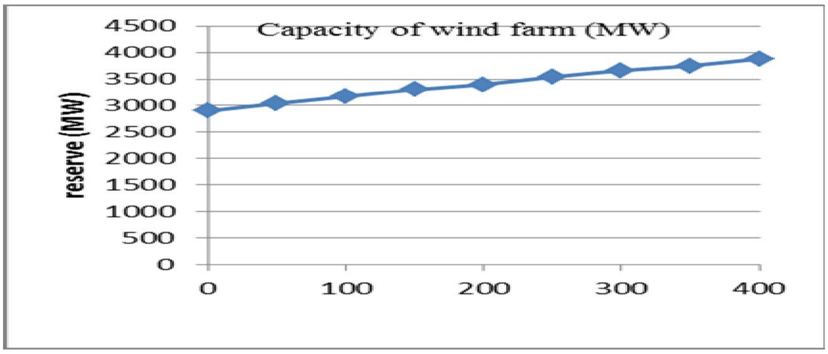

Figure (7): reserve of requirement in one day.

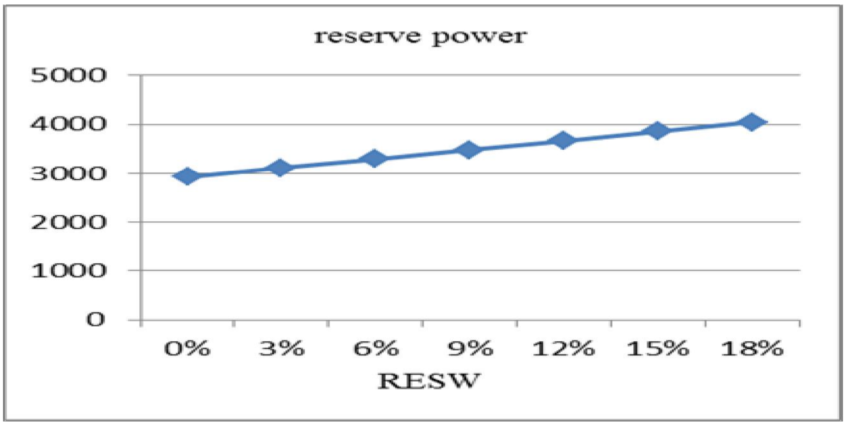

Figure (8): reserve of requirement with RESW

VII. Simulation 2

In this part we consider a 3 bus test system that has 2 conventional generators in bus 1 and 2. Generator 1 is cheaper than generator 2. So generator 1 is more commitment than generator 2.

Data about test system is explained in [11].constraints of line and bus voltage and angle bus is considered. We consider 3 scenarios for wind farm. At first, we suppose that wind farm is located on bus 1. In this condition, because of network constraint (capacity of line) output power of generator 1 is decrease and output power of generator 2 is increase. For comparing level of wind turbine on cost of operation, we use Local Marginal Cost (LMP) for each bus. We suppose that output power of wind farm increase from 0 to 40 MW. Table 1 shows LMP for each bus with increasing level of output power of wind. As we expected LMP in bus 1 is decrease, because output power of generator 1 is decrease and cost of wind is free. LMP in bus 2 is constant but LMP in bus 3 increase, because of constraint of line between bus 1 and 3, generator 2 is more commitment in this situation. Now we suppose that wind farm is located at bus 2. Table 2 shows LMP each bus. We realize that in this mode, LMP of buses 2,3 are decrease because output power of generator 2 is decrease and LMP of bus 1 is constant.

Now, suppose that wind farm located at bus 3. In this condition, LMP of bus 2,3 is decrease but LMP of bus 1 is increase. Because of in this mode, structure of network and KVL in system set the power of network. in this mode output power of generator 1 is decrease.

Table 1: LMP each bus ($/MWh)

PWIND	0MW	10 MW	20MW	30MW	40MW
bus1	21.8	19.8	17.8	15.8	13.8
bus2	46.9	46.9	46.9	46.9	46.9
bus3	72	74	76	78	80

Table 2: LMP each bus ($/MWh)

PWIND	0MW	10MW	20MW	30MW	40MW
bus1	21.8	21.8	21.8	21.8	21.8
bus2	46.9	44.9	42.9	40.9	38.9
bus3	72	68	64	60	56

Table 3: LMP each bus ($/MWh)

PWIND	0MW	10MW	20MW	30MW	40MW
bus1	21.8	23.8	25.8	27.8	27.8
bus2	46.9	42.9	38.9	34.9	27.8
bus3	72	62	52	42	27.8

VIII.Conclusions

This paper considers the impact of wind power forecasting on unit commitment and economic dispatch. Two unit commitment methods are tested in trying to evaluate the uncertainty in the wind power output. results show that wind power forecasting errors have great impact on the scheduling of generating units in the day-ahead market for the real-time dispatch. The UC problem is firstly solved as a deterministic optimization problem. Secondly, the uncertainties of the wind power generation is simulated. It is shown that this uncertainty has great impact on reserve requirement in the network and extremely depended to error of forecasting. Then impact of wind farm and location of it on LMP of buses considered.

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