Estimation of Operating Reserves for High Wind Penetration Systems using Reliability based Analysis

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Abstract: With the addition of variable energy sources into the electric power system, the way in which the system is planned and operated in the past needs significant change. The main effect is on balancing the supply and demand due to the increase in variability and/or uncertainty and hence operating reserves which are used to balance supply and demand need significant system wise analysis. Power system operators are evolving alternate approaches, changing the rules and practices to take care of new trends of complexities. In this paper a new methodology has been proposed to estimate the required operating reserves in the system with high penetrations of wind power through reliability analysis which would be useful to the system operators. This estimation of operating reserve directly helps for scheduling programs which are used to schedule conventional units. The methodology considers generation outages; system load forecast errors; low and high wind seasons; variability and uncertainty of variable energy sources. The proposed methodology is first applied to RBTS for validation and studies are performed on IEEE-RTS and practical power system, where high penetration of wind power exists. The results illustrate that the need of dynamic operating reserves for power systems where high penetration levels of wind generation exists.

Key words: *High wind penetration, IEEE-RTS, Monte-Carlo simulation, normal distribution function, operating reserve, unit commitment risk index, wind variability and uncertainty.*

1. Introduction

In power system, generation must be close to the demand to ensure the system frequency is maintained at or very close to specified levels. If variable generation and demand conditions could be predicted in advance, meeting these requirements would be relatively straightforward. However, many of the power system components, including generation unit forced outages, sudden load changes, and transmission equipment availability are variable and unpredictable. Therefore, additional generation facilities above the need (to meet actual demands) are made available either on-line/on-standby generally referred as operating reserve. Operating reserve allows system operators to compensate for unpredictable imbalances between generation and demand caused due to sudden outages of generating units, changes in generation from variable sources, uncertainty in load forecasting and unexpected deviations by generating units from their production schedules.

Power system operators across the world are evolving alternate approaches to understand the operating reserve requirements with high penetration of variable generation resources. This is due to the fact of increasing the number of stochastic/random behaviors in the system with variable energy sources.

The probabilistic methods in planning phase are well developed in the literature [1]-[3] and are used for practical applications [4], [5] as compared to operational phase. The applications of alternate approaches for operational issues have been addressed in recent times with wind energy sources [6]-[10], [13]-[17]. Majority of the probabilistic approaches are based on the PJM method [21] and have addressed the operating issues with wind integrated system systems with different approaches.

Statistical method such as Auto Regressive Moving Average (ARMA) has been applied in [7] for the wind sites to simulate wind turbine power curve to assess the risk of short term wind power commitment. A sequential Monte-Carlo simulation technique was utilized in [8] to analyze the system risk by simulating hourly wind speeds using ARMA time series model. Instead of using a single wind turbine power curve, an entire wind farm power curve was used to represent the operational parameters of individual wind turbine generation units located in that wind farm [8].

The impact of integrating wind generation on the regulation and load following requirements of the California power system was discussed is [9]. The paper considers wind and load forecast errors in its mathematical model which in turn are used in scheduling, real-time dispatch, and regulation processes. An attempt of combining the traditional and probabilistic methods has been made in [10].

The probabilistic way of wind modeling was added to the traditional unit commitment and economic dispatch model. This paper addresses the advantages over classical methods [11] and [12] where wind power has been modeled as negative load.

Different wind speed modeling techniques using hourly observed wind speed data, hourly mean wind speed data, ARMA time series [7], [8], moving average time series, normal distribution, and Markov chain models for probabilistic methods are explained in [13]. The probabilistic methods considering conventional unit outages, load forecast uncertainty and wind power forecast uncertainty has been used in [14], [15] to determine the amount of operating reserves in the system.

Statistical methods considering the wind and load forecast uncertainty were reported in [16] and [17] to analyze the effect of wind integration on operating reserve. The wind power forecast error almost follows a Gaussian distribution or normal distribution as presented in [14], [25]. Standard deviation (σ) of uncertainty in load and wind power with confidence interval of ±2σ and ±3σ [17] have been reported as the preferred metric to calculate load following requirements for wind. The statistical indices are used in [18]-[20] to determine the system ramp up and ramp down requirements and same is suggested for operating reserve requirements and conventional unit scheduling.

The modeling of wind power presented in above literature is poised with difficulty in the practical scenario when wind penetration level increases. Further, including wind speed forecast in the modeling of each individual wind turbine operating horizon would be difficult as there would be thousands of wind turbines in the practical domain (in the considered practical case there are more than 10000 wind turbines). This paper addresses the application of probabilistic methods using Monte-Carlo simulation technique for power system with generation mix of thermal, hydro and wind sources. Flexible energy sources in the system like hydro generators are modeled in Monte-Carlo simulation. The region wise modeling of wind generation has been incorporated as normal distribution function considering the wind power forecast values with forecast uncertainties observed in the past. The method has been applied to analyze IEEE-RTS system by adding wind power data from practical power system. Further the analysis is extended to one of highest wind penetration states (wind installed capacity is around 40% of total installed capacity) in INDIA to analyze the increase in requirement of operating reserve with high wind penetration levels.

2. Methodology

In PJM probabilistic approach [21], the Unit Commitment Risk (UCR) index is defined as the probability of just carrying or failing to carry the expected load during a specified time into the future, designated as the lead time. An assumption is made that any assistance to increase the reserve margin can only be obtained after a specified lead time. This is the time required to start and synchronize with additional units. The lead time required to place a unit in service is dependent upon many factors, the most important being the type of unit. Thermal units can take several hours depending on their prior operating history while hydro and gas turbine units require much shorter times. This paper uses this index and extended the analysis by incorporating the wind generation. A new methodology for modeling wind generation is proposed to determine the increase in operational reserves due to the addition of renewables in the system which is very important for system operators to maintain the load-generation balance during power system operation.

The adopted and proposed modeling of system modeling has been presented below. Flowchart has been presented at the end of the methodology to describe the developed program for validation and analysis of presented cases.

A. Thermal Generating Unit Model

The methodology presented in [21] considers the probability of generator outages on an hourly basis. The full outage probability (λ) of a unit is the probability that the unit will stop providing all of its current output in an hour period. Here it is assumed that the unit tripping causes the units output to be instantaneously unavailable.

$$\lambda = \frac{failure\ rate/year}{8760} \dots\dots\dots\dots\dots\dots\dots\dots (1)$$

The most common model for a conventional generating unit is a two-state representation in which the unit is either in the up or down state. If the failure and repair times are exponentially distributed, the probability of finding a unit on outage at time t given that the unit is available at time t= 0 is given by

$$P(down) = \frac{\lambda}{\lambda + \mu} - \frac{\lambda}{\lambda + \mu} e^{-(\lambda+\mu)t} \dots\dots (2)$$

where,

λ and μ are the failure and repair rates respectively,

t is lead time - during this time, the system operator cannot start non-spinning reserve units. He can only count on the existent spinning reserve in the generation units that are spinning. This lead time may range from few minutes to hours, depending on how the operating reserves are defined and also on unit type. Typically values vary from 1 to 6 hours.

Repair of a failed unit is not generally possible in a short lead time, hence the above equation becomes,

$$P(down) = 1 - e^{-\lambda t} \dots\dots\dots\dots\dots\dots\dots.(3)$$

If the lead time is very short i.e. 1 to 6 hours, then λt <<1 and then,

$$P(down) \approx \lambda t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(4)$$

The probability of the unit failing during the lead time, t, is known as the Outage Replacement Rate (ORR) [21] and is applied in the basic PJM method. The ORR parameter is similar to the forced outage rate (FOR) used in planning studies. The only difference is that the ORR is not simply a fixed characteristic of a unit but is a time-dependent quantity affected by the value of lead time being considered. The risk associated with just carrying or failing to carry a specified load level can be obtained from the cumulative probabilities associated with the various capacity outage levels for the scheduled units. The generating units can be represented by two state or multi-state models for analysis using Monte-Carlo simulation [5], [22].

B. Peak or Hydro Generating Unit Model

Hydro units which are used for peaking units operate for relatively short times and are frequently started and stopped. The model of a base load unit is inadequate for modeling peaking units. The main reason is when the unit is forced out of service, it may not be needed by the system, and when it is in the operating state, periods of service may be interrupted by reserve shutdown. The 'IEEE Task Group on Models for peaking Service Units' proposed the four-state model [23] to model the peak load units or hydro units. However, the modeling of hydro units in most of the practical conditions is limited by energy constraints and unavailability of data [24]. Hence the status of the hydro units are simulated by considering their forced outage rate, system load level, the power output from conventional units and wind farms, and the energy limitation imposed by water availability. The energy availability has been considered from past history of water availability [21].

C. Wind Generation Model

The accuracy of the load and wind power forecasts will have a significant effect on calculation of system reserve levels as they introduce greater uncertainty on the system [25]. The wind power forecast error almost follows a Gaussian distribution or normal distribution [14], [25]. Hence the stochastic nature of the wind power forecast error has been modeled as normal distribution function with mean and standard deviation (σ) for each hour from the historical wind power data as presented in Fig. 1. The probabilistic methods like Monte-Carlo simulation method can simultaneously consider the stochastic nature of this variation in wind power along with demand variation. In simulation, the normal distribution function is constructed as shown in Fig. 1 up to ±3σ using modified Box–Muller transform technique [26] from wind power forecast data with Wind Forecast Uncertainty (WFU) observed from historical data.

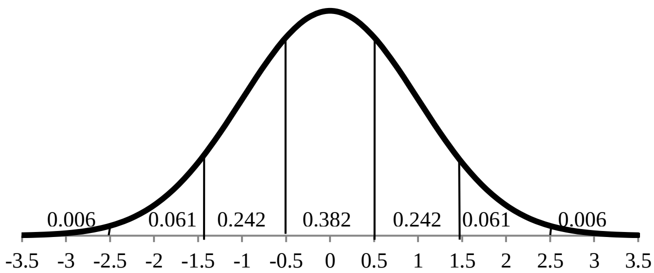

Fig. 1. Seven step approximation of the normal distribution

The developed algorithm for modeling of wind generation is presented below.

Step1: Generate uniform random numbers U_1, U_2 in the range of $[0, 1]$

Step 2: Generate random numbers v_1, v_2 such that,

$$v_1 = (2 * U_1) - 1;\ v_2 = (2 * U_2) - 1$$

Step 3: Calculate $r = v_1^2 + v_2^2$

Step 4: If $r \geq 1$, then go to step 1;

Otherwise Calculate,

$$X = v_1 \left[\frac{-2\ln r}{r}\right]^{\frac{1}{2}} \;, Y = v_2 \left[\frac{-2\ln r}{r}\right]^{\frac{1}{2}}$$

Step 5: Use generated random number X or Y for hourly simulation of wind power in Monte-Carlo simulation.

D. Load Forecast Uncertainty

In practice as the forecast is normally predicted on past experience, some uncertainty can exist. The load forecast uncertainty (LFU) can be included in the risk computations by dividing the load forecast probability distribution into class intervals, the number of which depends upon the accuracy desired [1]. Load forecast uncertainty has been modeled like a normal distribution probability distribution function [1].

E. Flowchart

The flowchart of the modeling procedure is presented in Fig. 2. The flowchart is presented per iteration and the same procedure is repeated till all iterations are complete. The above procedure can be later extended to required number of hours considering the coupling constraints between hours like energy constraints of hydro units.

3. System Data & Analysis

The Monte-Carlo simulation program has been developed based on the procedure presented in previous sections and has been validated with Roy Billinton Test System RBTS [27] and the validation results are presented in Table I. The results are in line with published results and fourth decimal errors are due to the stopping criteria adopted in Monte-Carlo Simulation [1].

Table I: Validation with RBTS

Case ID	Base Load Unit Ins. Cap. in MW	Load in MW	UCR index (published) [27]	UCR index (Developed program)
1	190	180	0.01307835	0.0131240
2	190	170	0.01127246	0.0112830
3	190	160	0.00684857	0.0068949

The computational algorithm presented in section-2 is applied to two test systems. The first test system is IEEE Reliability Test System (RTS) with additional wind details considered from practical system data. The second system is a practical power system in southern India where wind installed capacity is around 40% of total system installed capacity.

A. IEEE RTS

The IEEE RTS [28] contains 32 generating units with an installed capacity of 3405 MW with annual peak load of 2850 MW. The individual unit generation capacities, failure rates and Outage Replacement Rate (ORR) with corresponding lead times are given in Table II and all other data is considered from [28].

Base case simulation has been performed considering the data presented in Table II to find out the UCR index. The base case results of IEEE-RTS are presented in Table III. Deterministic criteria of maximum unit size as operating reserve has been considered to find the UCR index value, as RTS data presented in Table II has been modeled as base load units in simulation.

Table II: Generation data of IEEE RTS

Unit Size (MW)	Type and (No of units)	MTTF (hrs)	Failure rate/year	Failure rate/hour	Lead time (hrs)	ORR
12	Oil (5)	2940	2.9796	$3.401 * 10^{-4}$	4	$1.361 * 10^{-3}$
20	Oil (4)	450	19.466	$2.222 * 10^{-3}$	4	$8.889 * 10^{-3}$
50	Hydro (6)	1980	4.4242	$5.051 * 10^{-4}$	4	$2.020 * 10^{-3}$
76	Coal (4)	1960	4.4694	$5.102 * 10^{-4}$	4	$2.041 * 10^{-3}$
100	Oil (3)	1200	7.3	$8.333 * 10^{-4}$	4	$3.333 * 10^{-3}$
155	Coal (4)	960	9.125	$1.042 * 10^{-3}$	4	$4.167 * 10^{-3}$
197	Oil (3)	950	9.2211	$1.053 * 10^{-3}$	4	$4.211 * 10^{-3}$
300	Coal (1)	1150	7.6174	$8.696 * 10^{-4}$	4	$3.478 * 10^{-3}$
400	Nuclear (2)	1100	7.9636	$9.091 * 10^{-4}$	4	$3.636 * 10^{-3}$

where, MTTF = Mean time To Failure

The technique represented in flow chart is applied for IEEE-RTS with different alternatives, like variation in wind penetrations during low and high wind seasons. Case studies for different wind penetration levels along with load and wind forecast uncertainties have been performed to find the effect of wind power on operating reserve requirements. The base case study results of RTS are presented in Table III.

From Table III, it is observed that the value of UCR index for 400 MW reserve is around 0.00095.

This index value has been considered as the reference index throughout RTS analysis for calculating the operating reserves for the systems with different wind power penetration levels. From Table III, it is also observed that operating reserve is increasing with load forecast uncertainty. This case study results have been further used to find the effect of wind penetration along with wind forecast uncertainty on operating reserves.

Table III: Base case Results of IEEE-RTS

Case ID	Base Load Unit Ins. Cap. in MW	LFU (% of Load)	Load Met in MW	UCR index (Developed program)	Reserve (MW)	% Reserve
1	3405	0	3105	0.00095	400	11.75
2	3405	2	2905	0.00095	485	14.24
3	3405	5	2810	0.00095	595	17.47

The analysis with 21% of wind penetration is performed for high and low wind seasons respectively. The analysis has been performed for 24 hour duration with hourly intervals. The hydro generation units (6x50 = 300 MW) presented in Table II have been considered as peak load units with energy constrained to 55% for each unit. The hourly wind power data is considered from the practical power system [30] and is scaled to installed capacity of 900 MW (9 wind farms each having a capacity of 100 MW) to add IEEE-RTS. With this combination, wind: 900 MW, peak load units: 300 MW, base load units: 3105 MW, wind penetration level works out to be around 21% (900*100/ [900+300+3105]). The wind forecast uncertainty has been represented in percentage of maximum wind capacity (in this case peak wind capacity is 555 MW and 182 MW during high and low wind seasons respectively). The wind power for low and high wind seasons along with demand profile (demand data is considered from [30]) are presented in Fig. 3.

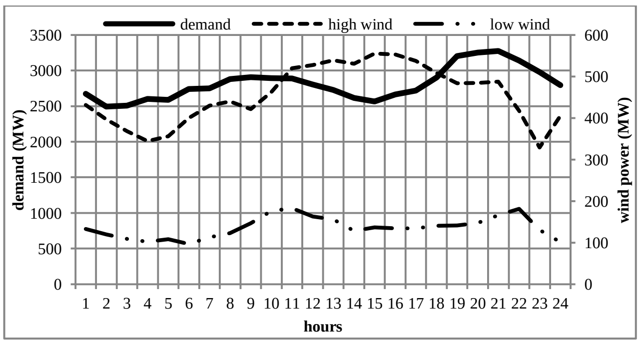

Fig. 3. Wind and Load profile for one day (during high & low wind season)

From Fig. 3, it can be noted that the availability of wind is more during the off-peak load and less during peak-load interval. This kind of high wind penetration profile along with demand profile poised to have more system complexities during the system integration and generation schedules. The peak wind power during high wind season for the installed capacity of 900 MW is 555 MW during 24 hours duration. This value has been considered along with thermal and hydro capacity for representation of operating reserve in percentage.

The study analysis with 21% of wind penetration is presented in Table VI and Table V for high and low wind seasons respectively. The wind forecast uncertainty has been represented in percentage of maximum wind capacity (in this case, 555 MW and 182 MW during high and low wind seasons respectively).

Table IV: Results of IEEE-RTS with 21% wind penetration during High Wind Season

Case ID	Ins. Cap. Of Base + Peak + Wind units in MW	WFU (%)	LFU (%)	Load Met in MW	Reserve in MW (in %)	Increase in reserve with wind addition in MW
4	3105 +300+900	10	0	3415	545 (13.7%)	145
5	3105+300 +900	10	2	3380	580 (14.7%)	92
6	3105+300+900	10	5	3245	715 (18%)	117
7	3105+300+900	5	0	3450	510 (13%)	110
8	3105+300 +900	5	2	3390	570 (14.4%)	82
9	3105+300+900	5	5	3245	715 (18%)	117

Table V: Results of IEEE-RTS with 21% wind penetration during Low Wind Season

Case ID	Ins. Cap. Of Base + Peak + Wind units in MW	WFU (%)	LFU (%)	Load Met In MW	Reserve in MW (in %)	Increase in reserve with wind addition in MW
10	3105 +300 +900	10	0	3140	447 (12.5%)	47
11	3105+300 +900	10	2	3072	515 (14.4%)	30
12	3105+300+900	10	5	2955	632 (17.6%)	37
13	3105+300+900	5	0	3154	433 (12.1%)	33
14	3105+300 +900	5	2	3080	507 (14.1%)	22
15	3105+300+900	5	5	2955	632 (17.6%)	37

From Table IV and Table V, it is observed that the operating reserve has increased more during high wind season as compared to low wind season. This is due to the reduction in net demand (demand – wind) uncertainty during low wind season. By referring to case-4 and case-10 with case 1, the raise in operating reserve comes to around 16% (145*100/900) and 5% (47*100/900) of wind installed capacity. Whereas wind capacity addition to the system is around 310 MW (3415-3105), i.e. 34.5% (310*100/900) and around 35 MW (3140-3105), i.e. 4% (35*100/900) during high and low wind seasons respectively. Hence the increase in operating reserve is minimal during low wind seasons (or low wind penetration) as compared to high wind penetration levels as capacity credit from wind energy is low. Table VI shows the study results for the system with very high wind penetration level of around 40%.

TABLE VI: Results of IEEE-RTS with 40% Wind Penetration during High Wind Season

Case ID	Ins. Cap. of Base + Peak + Wind units in MW	WFU (%)	LFU (%)	Load Met In MW	Reserve in MW (in %)	Increase in reserve with wind addition in MW
16	3105 +300 +2300	10	0	4080	744 (15.4%)	344
17	3105+300 +2300	10	2	4040	784 (16.2%)	299
18	3105+300+2300	10	5	3870	954 (19.8%)	359
19	3105+300+2300	5	0	4190	674 (14%)	274
20	3105+300+2300	5	2	4085	739 (15.3%)	254
21	3105+300+2300	5	5	3920	904 (18.7%)	309

From these case studies with IEEE-RTS, it is observed that operating reserve requirements depend on the wind penetration levels, wind seasonal effects and uncertainty levels of load and wind forecast.

Practical System Study

The studies have been performed for one of the high wind penetration states where the wind installed capacity is around 7300 MW. The total installed capacity of the state including wind is 17540 MW. This works out to be around 42% (7300*100/17540) of the installed capacity. The hydro units installed capacity of the system is around 2220 MW and the rest of the generation comes from coal, gas, diesel base units [29] – [30].

Hydro units are modeled as energy limited units where energy has been calculated from the past history. Base load and wind power units has been modeled based on the model presented in section-2.

The study results along with the operating reserve requirements have been presented in Table VII and Table VIII for high and low wind seasons respectively. All case studies have been performed for 24 hour duration with corresponding energy constraint for energy limited units. The raise in operating reserves with the addition of wind power is presented while comparing with deterministic criteria of largest unit in the system as operating reserve as detailed the procedure in IEEE-RTS system analysis. The UCR index for the base case (considering only thermal units) is around 0.0085. This index has been considered as reference index value and used for calculation of operating reserves for the system with wind generation.

TABLE VII: Results for Test System-2 during High Wind Season

Case ID	Ins. Cap. of Base + Peak + Wind units in MW	WFU (%)	LFU (%)	Load Met In MW	Reserve in MW (in %)	Increase in reserve with wind addition in MW
1	11210+1880+0	---	0	10654	556 (5%)	---
2	11210+1880+0	---	2	10482	728 (6.5%)	---
3	11210+1880+0	---	5	9916	1294 (11.5%)	---
4	11210+1880+7300	10	0	16400	1860 (10.2%)	1304
5	11210+1880+7300	10	2	16107	2153 (11.8%)	1425
6	11210+1880+7300	10	5	15298	2962 (16.2%)	1668
7	11210+1880+7300	5	0	16673	1587 (8.7%)	1031
8	11210+1880+7300	5	2	16368	1892 (10.4%)	1194
9	11210+1880+7300	5	5	15474	2786 (15.2%)	1492

TABLE VIII: Results for Test System-2 during Low Wind Season

Case ID	Ins. Cap. Of Base + Peak + Wind units in MW	WFU (%)	LFU (%)	Load Met In MW	Reserve in MW (in %)	Increase in reserve with wind addition in MW
10	11210+1880+7300	10	0	13827	1013 (6.8%)	457
11	11210+1880+7300	10	2	13656	1184 (8%)	456
12	11210+1880+7300	10	5	12985	1855 (12.5%)	561
13	11210+1880+7300	5	0	13856	984 (6.6%)	428
14	11210+1880+7300	5	2	13699	1141 (7.7%)	413
15	11210+1880+7300	5	5	13038	1802 (12.1%)	508

The study results presented in Table VII and Table VIII show that the raise in operating reserve with the addition of wind power into the system strongly depends on the uncertainty in wind and load forecasts. It is also observed that the system operating reserve depends on the amount of wind power availability (seasonal effect) and its uncertainty levels.

From the above study case with EFU of 10% and LFU of 5% (case 6), the maximum required reserve for the system is 16.2% as compared with 11.5% (case 3) where no wind power is considered. Also note that, even though the reserve increases due to addition of wind power into the system, wind power contributes to improve capacity credit of the system which in turn reduces the capacity shortage in the system.

Hence the improvement in uncertainties during forecasting will improve the system operation aiding in better operating reserve management and generation scheduling.

4. Conclusion

This paper proposed a new methodology for estimating the operating reserve and also evaluates the raise in operating reserve due to the addition of wind energy at high penetration levels. Operating reserve estimation by deterministic methods considers the largest unit or largest unit and second largest unit size. This does not hold good for the system having stochastic variables like renewable energy sources. Also the statistical methods used by most of the utilities for operating reserve like confidential risk of 2σ or 3σ [17] of wind forecast error suffers with disadvantages like not considering the net effect of wind uncertainty and load uncertainty simultaneously with generation mix contributions. The probabilistic method presented in this paper can be used for practical power systems to find the operating reserves which dynamically vary every day/hour. The model presented considers the contributions from generation mix and wind variation along with load including their corresponding uncertainties.

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