

A New Method to Evaluate the Optimal Penetration Level of Wind Power

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Abstract—This paper introduces a new method for determining the optimal penetration of wind farms in power system adequacy assessment. Determining optimal penetration levels of wind farms based on the improvement in system reliability is an important factor in planning studies. However, this task requires repetitive calculations of the reliability indices and the capacity value of wind power. In this work, a real genetic algorithm (GA) is used in conjunction with the discrete-convolution-based reliability evaluation method to calculate the optimal size of wind power installations. The maximum capacity value of wind power and system reliability improvement are used as a criterion to calculate the optimal size of wind power penetration level. The proposed method is applied on the IEEE reliability test system (IEEE-RTS). The results show that the optimal capacity value strongly depends on the penetration level and the reliability index that is used to determine the capacity value.

Index Terms—Capacity value, generation adequacy, genetic algorithm, wind energy.

I. INTRODUCTION

Due to socio-economic factors, renewable energy resources such as wind power have been replacing conventional generation. Wind turbines differ from conventional generators in terms of capability and dispatchability. Also, wind farms comprise a multitude of wind turbine generators (WTGs) that spread out over a large geographic area, and their output power cannot be consistently made available due to dependency on the availability of the input (wind speed).

Despite the advantages of wind power, the operational characteristics of WTGs pose a substantial challenge to the operation of the main grid especially with high penetration levels. For example, several challenges such as reliability and security of the main grid and power quality have been extensively reported in the literature [1], [2]. With high penetration level of wind power, measuring long term contribution of such resources has become a point of interest. This largely because of the intermittent and stochastic nature of wind power. In this context, reliability methods used for power system adequacy assessment play a major role in assessing the contribution of such resources to power grids. One of the important factors in the planning studies is determining of the optimal size of new installations of wind farms: *the nameplate capacity of a*

wind farm at the proposed location that provides a maximum contribution to system generation adequacy.

One of the widely used approaches in measuring the contribution of wind power to support load demand is the capacity value. The capacity value of a wind farm is the capacity of a dispatchable resource that, when used instead of the wind farm, results in the same level of system reliability. Reliability methods are usually considered to be more suitable in evaluating the capacity value of variable resources such as wind power, as they count for the stochastic behavior of such resources [3]. In determining the capacity value of wind power, the effective load carrying capability (ELCC) approach has been favorably used among the available criteria [4].

The common practice of the existing methods is the use of the reliability indices such as LOLE (loss of load expectation) index as a criterion to determine the capacity value of variable resources. The ELCC measures the peak load carrying capability (PLCC) of the generation system after the addition of wind power to the system. The PLCC of a power system represents the peak load that the system can supply by the available generating units while maintaining a predefined reliability target [5]. The ELCC is traditionally performed using iterative processes where the loading level of a system is linearly incremented by a certain amount, usually a constant step of load, until the targeted reliability index reaches a specified level. In this process, two metrics are used: loss of load probability (LOLP) and loss of load expectation (LOLE). Other reliability indices such as loss of load frequency (LOLF) are rarely considered.

In the literature, several criteria have been introduced to determine the optimal size of variable resources that can be integrated into the grid. In [6], [7], the penetration level of variable resources is evaluated based on their contribution to energy market. In [8], [9], the maximum penetration level of wind power is evaluated based on the adequate frequency response of the system. In [10]–[12], the voltage stability and transmission system constraints are considered for evaluating the maximum penetration level of wind power. Others have considered operational and economic factors to evaluate the optimal location wind turbines [13], [14].

Determining the optimum sizes of wind power in system generation adequacy assessment, in terms of their capacity values, has not been given much attention; using iterative methods would be extremely complex and computationally expensive as they require several runs for every candidate installed capacity. However, population based intelligent search methods can be implemented to determine the optimal capacity value of wind power.

In this paper, a real genetic algorithm (GA) is used in conjunction with the discrete convolution to evaluate the optimal size of wind power installations. The capacity value of wind power and system reliability improvement are used as criteria to evaluate the optimal installations of wind farm. The optimal capacity value of wind power is evaluated based on their effective load carrying capability. The proposed method considers the effect of the input variability, forced outages of unconventional generation units, and correlation of the output of variable resources with system load.

The remainder of this paper is organized as follows. Section II discusses the capacity value of wind power and system modeling. Section III describes the use of the genetic algorithm in determining the optimal penetration level. Section IV presents the application of the proposed method. Section V provides some discussion and concluding remarks.

II. ADEQUACY ASSESSMENT AND CAPACITY VALUE

Generation adequacy assessment is generally used to evaluate system reliability indices for short-term and long-term generation capacity planning. In this work, the discrete convolution method is used to construct a generation model of the system by convolving the discrete probability distributions of generating units to construct a capacity outage probability and frequency table (COPAFT). In reliability analysis, generation and load models are needed to construct a generation reserve margin of the system from which the reliability indices are calculated.

A. Generation Model

For N generating units with known forced outage rates (FORs), the COPAFT is built using the *unit addition algorithm*. This is a recursive algorithm that starts with the distribution of one unit and successively convolves it with the distributions of the remaining units, one unit at a time.

In general, when adding a new unit of capacity C , the cumulative probability and frequency of an outage of X MW can be determined by the following expression [15], [16].

$$P(X) = \bar{P}(X)(1 - q) + \bar{P}(X - C)q \quad (1)$$

where $P(X)$ and $\bar{P}(X)$ denote the cumulative probabilities of the capacity outage state before and after the units are added respectively. Equation (1) is initialized as follows.

$$P(X) = \begin{cases} 1, & \text{if } X \leq 0 \\ 0, & \text{otherwise,} \end{cases}$$

The cumulative probability $P(X)$ for a forced outage of X MW or greater can be in general calculated using (2).

$$P(X) = \sum_i P(X_i), \quad \forall X_i \leq X \quad (2)$$

where

$$\bar{P}(X) = 1, \quad \forall X \leq C$$

The cumulative frequency of capacity outage of X MW can also be calculated using the same approach using (3).

$$F(X) = F_i(1 - q) + F_jq + (P_j - P_i)q\mu \quad (3)$$

where q and μ are respectively the probability of failure and repair rate of the new added unit; P_i , P_j , F_i , and F_j are determined from the old COPAFT (prior to adding the new unit); i is the index of the existing capacity outage state, $C_i = X$, and j is the index of existing capacity outage state, C_j , such that $C_j = X - C$. F_i and F_j are cumulative frequencies of states i and j respectively.

B. Load Model

The load model is usually expressed in the form of probability and frequency distribution of the random variable that represents system load. The load model can be constructed by scanning the hourly load data of the system over the time period of study, usually one year. In general, the load model can be built in terms of load level L_i with its commutative probability and frequency as follows [17].

$$P_L(L \geq L_i) = \frac{H(L \geq L_i)}{T} \quad (4)$$

$$F_L(L \geq L_i) = \frac{\Gamma(L < L_i \rightarrow L \geq L_i)}{T} \quad (5)$$

where $H(L \geq L_i)$ is the number of hours that the hourly load is greater than or equal to the load level L_i , T is the number of hours in the interval, $P_L(L \geq L_i)$ is the commutative probability of the load level L_i , $\Gamma(L < L_i \rightarrow L \geq L_i)$ is the number of transitions from $(L < L_i)$ to $(L \geq L_i)$, and $F_L(L \geq L_i)$ is the commutative frequency of L_i .

C. Reserve Margin Model

The generation reserve margin is used to calculate the reliability indices. The reserve margin model consists of the probability and frequency of a random variable M , which represents the difference between the available generation and load. Though the rigorous derivation of the reserve margin model will not be reproduced here, some expressions will be developed and explained by means of simple arguments to derive expressions for analytically determining the capacity value of wind power. The reserve margin model can be expressed in terms of generation and load model as follows [17].

$$M = C_c - C_O - L \quad (6)$$

where C_O is the capacity outage, L is the system load, and C_c is the net available generation capacity for commitment which can be expressed as follows.

$$C_c = C_i - C_{OP} \quad (7)$$

where C_i is the installed capacity, C_{OP} is the capacity on planned outage.

For each generation reserve margin level, M_i , the cumulative probability and cumulative frequency can be calculated using (8) and (9) respectively.

$$P(M \leq M_i) = \sum_{j=1}^{n_G} [P_G(C_j) - P_G(C_j + 1)] \times P_L(C_c - C_j - M_i), \quad (8)$$

$$F(M \leq M_i) = \sum_{j=1}^{n_G} [F_G(C_j) - F_G(C_j + 1)] P_L(m_{ij}) + [P_G(C_j) - P_G(C_j + 1)] F_L(m_{ij}), \quad (9)$$

where n_G is the number of states in the generation model (the COPAFT), C_j is the capacity outage level, $m_{ij} = C_c - C_j - M_i$, and $P_G(\bullet)$ and $F_G(\bullet)$ are the cumulative probability and frequency of the generation model respectively.

The proposed method is based on the fact that the capacity value of wind power is bounded between 0 MW and their installed capacity (rated capacity). Also, it is assumed that the increase in system load is evenly distributed on the load profile, which has been commonly used. Therefore, the capacity value can be calculated by augmenting the generation reserve margin by the maximum capacity of wind power. The augmented reserve margin model can be expressed in terms of generation, load, and wind power models using (6) and (7) as follows.

$$M_{au} = M + C_V, \quad (10)$$

where M is the generation reserve margin prior to adding wind and C_V is the available capacity of wind power.

The CDF of the augmented margin, CDF_{au} , is created in same manner as creating a CDF for the original margin. However, the range of the augmented reserve margin is from $-L$ to C_R instead from $-L$ to 0 of the original system (prior to adding wind power) where C_R is the maximum capacity of wind power. A typical CDF of an augmented margin is shown in Fig. 1. The CDF of the generation reserve margin of the original system crosses the zero level at $P(0)$. Now, since the capacity value is defined as the amount of load increase (after adding wind power) that would return a reliability index to its initial value (prior to adding wind power), the capacity value of a wind farm can be determined by projecting $P(0)$ to the augmented margin.

D. Wind Power Modeling

In the assessment of the effect of wind power on power system reliability, forced outages of wind turbine generators (WTGs) have a significant impact on the available power [18], [19]. Several studies have shown that the operation and environmental factors could lead to different failure modes of WTGs. Failures usually occur due to ageing, worn out parts

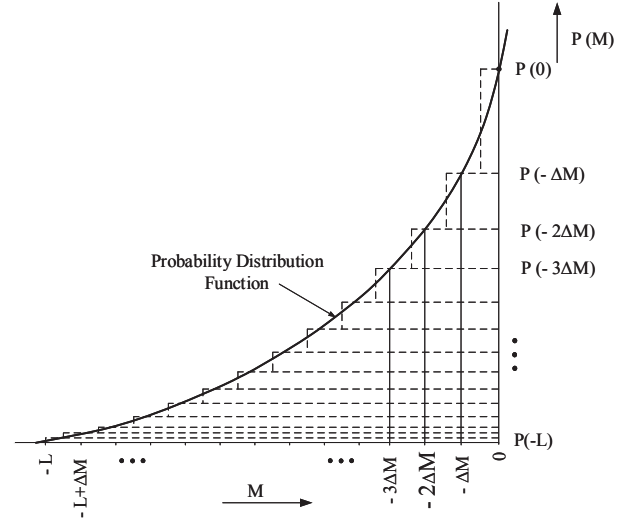


Fig. 1. A typical cumulative probability distribution function of generation reserve margin.

or manufacturing defects. Considering failures of WTGs as independent events, the probability of failure of WTG can be modeled as Markovian component with two states, up and down states with known failure and repair rates, λ and μ respectively (λ is the failure transition rate from an up state to a down state, and μ is the repair transition rate from a down state to an up state). In this work, the hourly output power of wind power constructed from the hourly wind speed is modified to consider the forced outages. To consider the impact of the input variation and the correlation with system load, the hourly output power of wind power is modified using the approach proposed in [20]. The following expressions are used to modify the hourly output power of wind power.

$$Cv_{i,j} = \frac{C(O_j)}{C_R} \times C(b_i) \quad (11)$$

where $Cv_{i,j}$ is the modified output power at hour i for the state j of the COPAFT of wind turbines, $C(O_j)$ is the available capacity in state j of the COPAFT of wind turbines, C_R is the total installed capacity of wind, and $C(b_i)$ is the output power at hour i .

E. Capacity Value of Wind Power

In measuring the contribution of variable resources such as wind power to the generation adequacy assessment of power system, capacity value based methods have been amply implemented. These methods can be classified into intelligent search methods [21], simulation methods [22], [23], and analytical methods [24], [25]. Further, these methods can be classified into iterative methods [21], [22] and non-iterative methods [5], [26]. The non-iterative method aimed to reduce the computational burden associated with the calculation of capacity value of variable resources. The proposed methods approximate the change in the the LOLE index versus load increase to calculate the capacity value. This approximation

may lead to considerable errors in calculating the contribution of variable resources [5]. In these methods, the ELCC based approach is widely adopted to measure the capacity value of variable resources [27]. The ELCC of a power generator measures its ability to effectively increase the generating capacity available to a system without increasing the loss of load of the system [27].

III. GENETIC ALGORITHM OPTIMIZATION

In this paper, two indices are used to evaluate the capacity value of wind power which are the capacity value based on LOLP (CV_P), and the capacity value based on LOLF (CV_F). The CV_P and CV_F are maximized with respect to the penetration level of wind power, P_W , and the the reliability indices (LOLP and LOLF) are minimized. Evolutionary algorithms such as genetic algorithm (GA), partial swarm, empire colonies and others have been commonly used in several optimization problems in power systems. Compared to classical optimization methods, evolutionary algorithms can easily handle discontinuity, multi-modality, and unknown features of objective functions. Moreover, evolutionary algorithms are more powerful in exploring the entire search space because they are based on evolution of a population of points in the search space.

Genetic algorithms and their implementations on power systems have been under intensive research and development. The basic and most popular genetic algorithm is the binary coded GA [28]. The binary coded GA is applied to the population through three operations which are selection, crossover, and mutation [29] within one generation. Selection operators choose the points (parents) to the mating pool using roulette wheel or tournament competition [29]; crossover operators generate new points (offspring) by exchanging the information between the parents via replacing the bits between the two crossed parents; the crossover for a pair of parents happens with a probability P_x . The mutation operator flips some of the points of the whole population at random with a probability P_t for each bit to be mutated. The offspring created from the crossover occupy the place of the parents in the intermediate generation; then the offspring created by the mutation occupy the places of their parents. By this operation, the current population is updated for the next successive generation.

The accuracy of the binary coded GA is directly related to the number of bits used for the entire variables. However, the real coded GA does not suffer from this problem because the evolutionary process is performed in the real space [30], [31].

The objective is to find the optimal penetration levels of wind power that have maximum capacity values for the factors CV_F and CV_P simultaneously. Since the goal is to maximize the the capacity values, CV_P and CV_F , and to minimize the reliability indices, LOLP and LOLF, the objective functions of a reliability index and its corresponding capacity value are combined in one fitness function using the weighted sum method. The real GA is applied with conjunction of discrete convolution to maximize the CV_P and CV_F and minimize LOLP and LOLF with respect to the penetration level of

wind power. The two objective functions of the two capacity factors are combined using the weighted sum approach to find a common optimal solution. The crossover equations are presented as follows [29].

$$C_i = \begin{cases} \frac{1}{2} \times [(1 + \alpha) \times P_i] + ((1 - \alpha) \times P_j) \\ \frac{1}{2} \times [((1 - \alpha) \times P_i) + ((1 + \alpha) \times P_j)] \end{cases} \quad (12)$$

where C_i is the offspring i , P_i and P_j are the randomly chosen parents pair; α is the distribution index. The mutation equations are given in the following equations [32].

$$rx = \begin{cases} [(2 \times rand)^{\frac{1}{1+N_m}}]^{-1}, & \text{if } rand \leq 0.5 \\ [1 - (2 \times rand)^{\frac{1}{1+N_m}}], & \text{if } rand > 0.5 \end{cases} \quad (13)$$

$$M_{i,j} = \begin{cases} [(P_{i,j}) + rx \times ((P_{i,j}) - P_{min,j})], & \text{if } rand \leq 0.5 \\ [(P_{i,j}) + rx \times (P_{max,j} - (P_{i,j}))], & \text{if } rand > 0.5 \end{cases} \quad (14)$$

where $M_{i,j}$ is the mutated veritable j for the i candidate, rx is the mutation variable constant, and $P_{max,j}$ and $P_{min,j}$ are the variable j global maximum and minimum respectively.

IV. CASE STUDIES

The proposed method is applied on the IEEE RTS [33]. This system has been extensively used in the literature for purposes of benchmarking. The IEEE RTS consists of 32 generating units with total generation capacity of 3405 MW and total peak load of 2850 MW. In these case studies, a typical wind turbine characteristic is assumed (type Vesta V90-3.0 MW [34]) and actual observed wind speed data is used [35]. The reliability data of the WTGs are as follows: The mean time to failure (MTTF) and mean time to repair (MTTR) are 3600 hours and 150 hours respectively. The MTTF lies in the ranges of actual WTGs, as reported in [36]. The MTTR is calculated from the forced outage rates and MTTF of WTGs.

In order to evaluate the optimal size of the wind farm, the observed wind speed data are utilized to calculate different nameplate capacities of the find farm. The real GA is used in conjunction with discrete convolution to evaluate the optimal size installations of wind farm.

For the crossover in the real space, the simulated binary coded GA introduced by [29], [37] is used with $P_x = 0.8$ and $\eta = 5$ which is recommended by [29]. The mutation is performed using polynomial mutation introduced by [32] with a mutation $P_t = 0.2$. To enhance the convergence of the algorithm to the optimal maximum, offspring replace their parents only if they have better fitness values.

A. Capacity Value and the Effect of Wind Power Penetration

In this case study, the effect of wind power penetration level on system reliability enhancement is evaluated. Fig. 2 shows the relationship between system LOLP and LOLF indices versus different levels of wind power penetration. As expected, as wind power penetration level increases, both LOLP and LOLF indices are improved. However, at high penetration level, system LOLP and LOLF indices showed a slight improvement compared to the case of low penetration level. The relation between system reliability and wind power

penetration level is also studied and is shown in Fig. 3. It can be seen from Fig.3 that as wind power penetration level increases, the capacity value decreases.

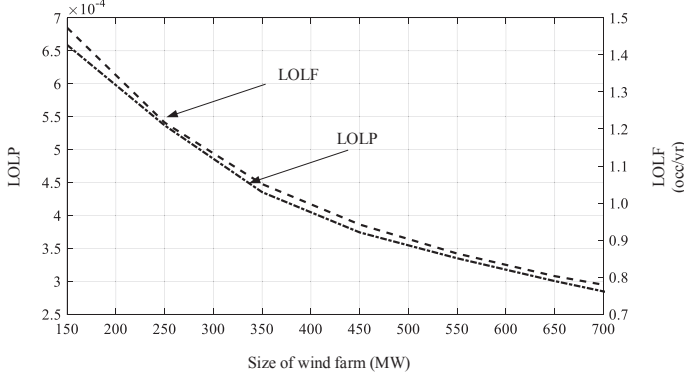


Fig. 2. System LOLP and LOLF indices with increasing of wind power capacity.

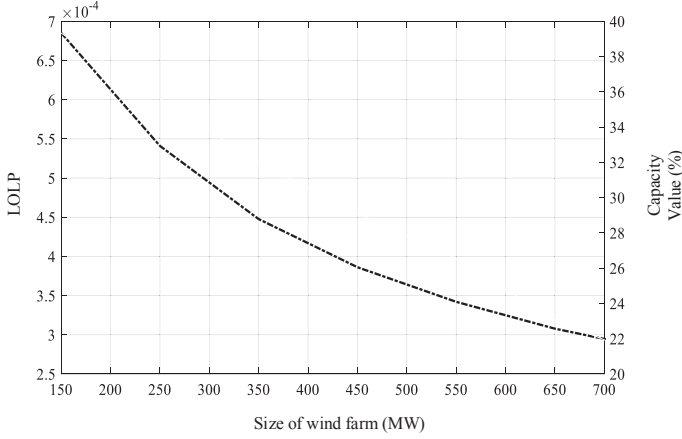


Fig. 3. Wind power capacity value versus system LOLP index

B. Optimal Penetration Level of Wind Power

The real GA is used in conjunction with discrete convolution to evaluate the optimal size of wind farm. As the wind power penetration increases, the capacity values, CV_P and CV_F , decrease; however, the system reliability indices improve. Since the goal is to maximize the the capacity values, CV_P and CV_F , and to minimize the reliability indices, LOLP and LOLF, the objective functions of a reliability index and its corresponding capacity value are combined in one fitness function using the weighted sum method. Note that, LOLP, LOLE, CV_P , and CV_F are functions of the wind farm nameplate capacity, P_W .

Three case studies for the reliability indices (LOLP and LOLF) and capacity values (CV_P and CV_F) are performed as follows:

- 1) Case Study 1: the optimal penetration level is evaluated by considering the two objective functions, CV_P and LOLP. In this case study, the percentage of importance

(wight factor) is 70% for the system LOLP index and 30% for the CV_P .

- 2) Case study 2: the optimal penetration level is evaluated by considering two objective functions CV_F and LOLF. In the case study, the percentage of importance (wight factor) was 70% for the system LOLF index and 30% to CV_F .

- 3) Case study 3: considering the combined fitness function of the four objective functions CV_P , LOLP, CV_F , and LOLF using wight factor of 35% for CV_P , 15% for LOLP, 35% for CV_F , and 15% for LOLF.

TABLE I
WIND POWER PENETRATION LEVEL AND ITS OPTIMAL SIZE

Case Studies	P_W (MW)	CV_P %	LOLP	CV_F %	LOLF (occ/yr)	Penetration Level
1	496.5	28.62	0.000354	24.36	0.8712	17.4%
2	484.5	27.30	0.000298	23.03	0.77043	17.0%
3	795.6	22.37	0.000264	17.90	0.70090	27.9%

The multiple criteria decision analysis is performed to measure the effect of wind power penetration level on the system reliability enhancement and the capacity value of wind power. The results obtained from the three case studies show that if the reliability indices of the system are given more weight than the system capacity value of wind power, case 1 and case 2, the optimal penetration level of wind power is less than the penetration level of wind power in the case 3, where the capacity value is given more weight in the evaluation criterion. The results also indicate that as the penetration level of wind power increases, the reliability indices are slightly improved.

V. CONCLUSION

This paper has introduced a new method to calculate the optimum wind power penetration based on capacity value. A real GA is used in conjunction with the discrete convolution method to determine the optimal size of new site installations of wind farms. The optimal capacity value is used as a criterion to determine the maximum installation size of wind farms. The proposed method was demonstrated on the IEEE RTS and the results are provided. The results have shown that the LOLP and LOLF indices produce different optimal capacity values. Also, the results have shown that the CV_P and CV_F are not correlated in terms of the capacity value with respect to the penetration level of wind power. Further, while system reliability indices improve as the wind power penetration increases, the capacity values (CV_P and CV_F) decreases. Choosing between these two criteria depends on the planning requirements and preferences.

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