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Reliability based power systems planning and operation with wind power integration: A review to models, algorithms and applications

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ABSTRACT

Wind energy has been considered as an important substitution of fossil-based energy for future society. However large-scale integration of wind power will introduce great risks to both power system planning and operation due to its stochastic nature. By adopting power system reliability theory, the risks can be quantitatively estimated so that numerous publications have been published to study reliability impacts caused by wind power. This paper thoroughly investigates the features of existing reliability models of wind power, reliability assessment algorithms and its applications in wind power related decision making problems. The paper also reveals significant differences existed in reliability models and algorithms between planning and operational phase of power systems, which are neglected in existing review articles.

Contents

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1. Introduction

Wind energy has been widely recognized as an important energy alternative of fossil fuel. Many countries, e.g. US, China, Germany and Denmark [1], have set various ambitious targets so as to integrate large scale wind power into their power systems in very near future. However, stochastic power output has become one major difficulty while planning or operating a power system with high wind penetration. Existing deterministic methods, which do not fully consider with uncertain factors, are no longer capable enough of evaluating system risks due to wind integration. Therefore it motivates researchers to look for stochastic-based methods for risk assessments.

One technical solution is of the theory of power system reliability, which was first proposed by Billiton [2] for quantitatively estimating impacts caused by component uncertainties, e.g. unexpected generator outages. Since the theory is suitable for studying stochastic factors, a large number of studies have been carried out based on its framework in order to estimate reliability performances of one power system with high wind penetration level. Literatures concerning this topic shall be carefully organized and reviewed for a better understanding on the development as well as the applications of the reliability theory on technical issues raised by stochastic wind power integration.

Many review works have been presented by several previous studies. Ref. [3] surveyed literatures from four different technical aspects, i.e. modeling of wind farms, methods of wind speed parameters assessment, reliability assessment algorithms as well as relevant factors affecting the reliability of wind power system (e.g. wake effect). Ref. [4] aimed at categorizing the reliability models of various kinds of renewable energy e.g. wind, solar as well as hydro power proposed from the published literatures. Similar review and survey works are also published in [5–7]. Literature [8] is focused on emphasizing the importance of reliability theory in long-term power system planning with large-scale integration of wind energy. Ref. [9] listed a series of uncertainties that would affect the integration of wind energy, such as energy storage capacity, market pricing and transmission ability and so on. However the paper did not present a thorough review to the approaches of estimating the risks of these uncertainties. A category of long-term wind power reliability models, which are the auto aggressive moving average (ARMA) models, were reviewed in [10]. Although these studies have provided excellent works, they are still insufficient for summarizing the state-of-art of reliability theory completely, which can be demonstrated from the following two aspects:

(1) Regarding power system planning phase. Most of previous review works only listed the basic ideas of available literatures in a much simple manner. However the features of models or algorithms are not clearly explained or further compared. That might result in difficulties for readers to find a best or most suitable model and algorithm for a specific problem. Meanwhile, some state-of-art works, involving reliability models and assessment algorithms proposed recently, are also not included in the existing reviews.

(2) Regarding power system operational phase. Previous review works are mostly concentrated on the studies about power system planning. In contrast, literatures concerning reliability-based system operation with wind power were not paid enough attentions. However, since stochastic wind integration has introduced significant risks within system operation, the concept of reliability is becoming more-widely accepted and recognized by system operators. In addition to that, the models as well as algorithms applied in operational phase are quite different from those in planning phase. Therefore these works shall be distinguishingly picked up and then carefully reviewed.

Under that background, this work is motivated by the purpose of compensating previous studies. We aim at presenting a more systematic literature review from the aspect of power system reliability concerning wind power. First, reliability models of wind power in planning and operation phase will be carefully investigated hence their characteristics can be revealed. Second, the reliability assessment algorithms in planning and operation phase will be reviewed. We focus on the algorithms which are being or potentially capable of being adopted to deal with the uncertainties of wind. And third, we review various kinds of reliability-based power system decision making problems when wind power is integrated. By doing so, the importance of reliability in modern power system can be demonstrated.

This paper is organized as followings: In Section 2 a brief introduction to power system reliability theory is provided in order to explain the basic concepts and theory architecture. Reliability-based power system planning with wind power integration is discussed in Section 3, which includes various applications, planning-phase reliability models of wind power as well as corresponding reliability algorithms. Section 4 investigates the reliability applications as well as corresponding models and algorithms under operational phase. At last Section 5 concludes the paper.

2. An introduction of power system reliability theory

The most fundamental function of modern power systems is to fully satisfy the load demand under every possible circumstance.

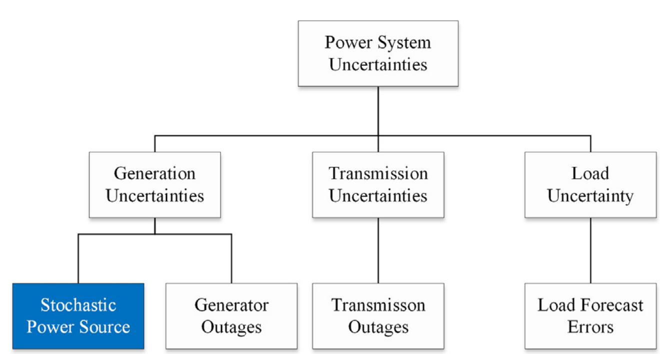

Fig. 2.1. Typical uncertainties in power system.

However the function is always being challenged due to various inevitable and unpredictable stochastic factors. Typical types of uncertainties are as shown in Fig. 2.1 [11]. Due to the reason, a theory which is capable of quantitatively estimating the risks is required. Therefore the system reliability theory is proposed and well-developed in the recent few decades, which can be applied for evaluating the impacts caused by stochastic factors.

The power system reliability theory focuses on estimating how power supplies are interrupted by uncertainties. The results can be reflected via the following reliability indices [12]:

(i) Expected energy not supplied (EENS): describing the annually energy which is not supplied to loads. This index is a representative of economic issues.
(ii) Loss of load probability (LOLP): describing the probability of load shedding. This index can be also described as the total hours of loss of load annually.
(iii) Loss of load frequency (LOLF): describing of the annually occurrence of load shedding events.
(iv) Loss of load duration (LOLD): describing the expected duration of each occurrence of load shedding. Longer LOLDs lead to more significant damage to electric customers.

The procedure of estimating the above indices is called reliability assessment, the first step of which is modeling stochastic elements. Element uncertainties can be either non-chronologically modeled or chronologically simulated. The second step of reliability assessment is selecting a proper algorithm. Due to various requirements imposed on reliability assessments such as accuracy or efficiency, various assessment methods are therefore proposed. These algorithms can be generally sorted into two categories as analytical algorithms and simulation methods.

The reliability theory has been highly recognized by power system industry for planning decision-making for long-term study, such as generation and transmission expansions, or reliability-centered maintenance scheduling [13]. However, regarding operational phase in short-term, the concept of reliability was not widely accepted due to a fact, that uncertainty of specific components (such as the outages of generators and transmission lines) in short-term are much smaller in operational phase of short-term than planning phase of long-term. That is, carrying out reliability analysis is unlikely to be necessary. The reason explains why reliability factors under operational phase are not considered by previous studies and industrial applications.

However, with the increasing risks introduced by stochastic renewable energy integration, reliability theory is playing a more significant role under operational phase in recent years. Therefore a lot of studies have been carried out concerning the operational reliability with renewable energy integration. A systematic review to such works, which is highlighted in Section 4, is hence becoming a major contribution of this paper.

3. Power system planning: Based on reliability assessment with wind power integration

In planning phases, reliability evaluation is always one major tool for power system decision makers. In order to carry out reliability assessments with wind power integration, the models and algorithms shall be studied first. There are three widely-accepted reliability models for wind power proposed in the past few decades. The features of these models are investigated in Section 3. Regarding reliability assessment algorithms, only those "*related to*" the issue of wind power integration are selected and then reviewed by this paper. The term of "*Related to*" is defined that the reviewed algorithms shall satisfy at least one of the following conditions:

(1) Algorithms which has been put into practice for assessing power system reliability considering wind power integration.
(2) Algorithms which has been considered as applicable for assessing power system reliability performances considering wind power integration.
(3) Algorithms which are considered to be capable of addressing reliability-related issues due to wind power integration by their authors.

If one algorithm satisfies one of the conditions, it is involved and reviewed in Section 3.2 of the paper. For other methods which have not been related to wind power study, this paper also gives a brief but comprehensive summarization.

In Section 3.3, major applications of reliability theory for power system planning are introduced. Finally a brief summary to the models, algorithms as well as applications is presented at the end of this section.

3.1. The reliability models of wind power in the phase of power system planning

The models under the planning-phase mainly deal with two stochastic factors, wind fluctuation and unexpected WTG outages. Three models are investigated in this section.

3.1.1. Multi-state capacity outage probability (COPT) model

The multi-state COPT model is the most fundamental model which has been widely adopted during power system planning. It is proposed by Giorsetto [14] from the foundation of conventional units models. The main idea of this model is described as follows.

A reliability model of WTG can be represented by a table called capacity outage probability table (COPT) according to the available generation capacity and corresponding cumulative probability. The elements in a COPT can be expressed as Eq (3.1) [14]:

$$(C_i, F(C_i)) = (C_i, prob(P(v, \lambda) \le C_i) \quad i \in 1, 2 \ldots N \tag{3.1}$$

where C_i is the average capacity in ith interval, N is the number of states. The probability feature for one individual WTG can be decided by the parameters of wind speed v and forced outage rate λ. Then wind farm model is derived through combining all wind turbines in together. By ignoring outage rates λ, Eq. (3.1) can be transformed into a simple Weibull distribution or Gaussian distribution.

The number of COPT states is also critical for reliability assessment. It is because more states usually means a better modeling accuracy as well as a higher computation overhead. In 2008, the study presented in [15] demonstrates that a 5-state COPT model is able to achieve a trade-off between accuracy and computation overhead. Therefore, a 5-state COPT model is considered as a default option for most of reliability assessment cases.

The EENS and LOLP indices can be easily computed with the model, however some other critical indices are not able to be obtained since the F&D (frequency and duration) indices of wind power variation are not modeled in the COPT model. For example the loss of load index of a system, which is strongly related to the durations and frequencies of load shedding events, cannot be accurately evaluated.

3.1.2. Multi-state Markov model

In order to improve the evaluation accuracy, a multi-state Markov model is proposed in 1996 [16]. The chronological wind power fluctuation are modeled by state transitions of a Markov model. By this model, not only the state probabilities but also the frequency and duration indices are able to be calculated and evaluated by

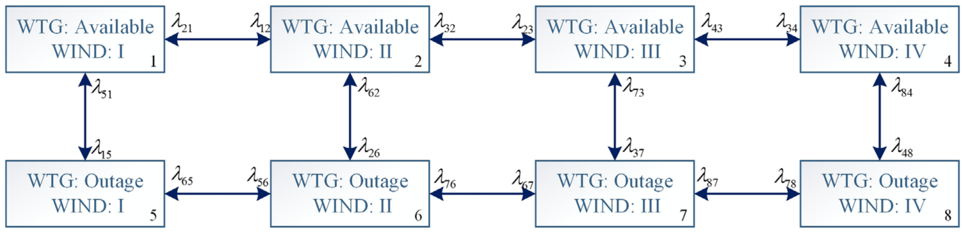

Fig. 3.1. State transition diagram of a WTG.

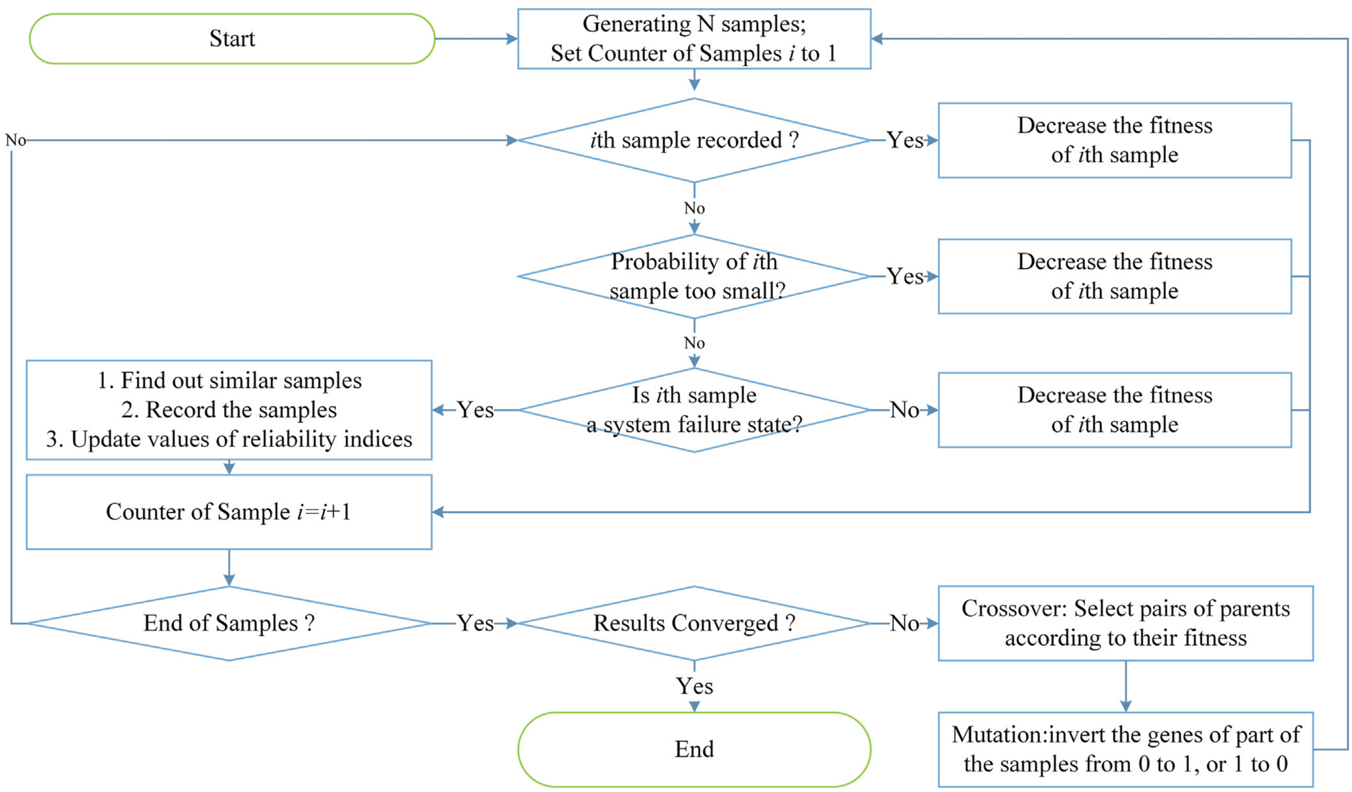

Fig. 3.2. The flowchart for genetic reliability assessment algorithm.

Markov-process methods. Therefore this model is more creditable and reliable for a power system reliability assessment.

Fig. 3.2 presents an example of the Markov model, which demonstrates a Markov state transition diagram of the output of a WTG. In Fig. 3.1, there are two possible states of a WTG and 4 possible states of wind speed. Each state is represented as a block while state transitions are as arrows.

The transition rates can be conveniently obtained through analyzing statistical data. By adopting the steady-state Markov process algorithm introduced in [16], the probability can also be easily calculated. Additionally, the frequency of occurrence as well as the duration of a state can be easily calculated with Eq. (3.2) [16].

$$F_i = p_i \sum_{j=1, j\neq i}^{N} \lambda_{ij}, \quad D_i = p_i/F_i = 1/\sum_{j=1}^{N} \lambda_{ij} \tag{3.2}$$

In order to illustrate Eq. (3.2), let us take State 7 in Fig. 3.1 as an example. The frequency of occurrence of State 7 is $F_7 = p_7(\lambda_{76} + \lambda_{73} + \lambda_{78})$ and the expected duration can be calculated as $D_7 = 1/(\lambda_{76} + \lambda_{73} + \lambda_{78})$. Since the F&D indices can be obtained, the Markov model is capable of compensating the COPT model.

Since chorological wind fluctuation is involved and described by the Markov model, it is considered as a more accurate model considering with more details than the COPT model. In addition, many other relevant factors such as wind spatial correlation, wake-effect [16] can also be conveniently considered and described by expanding the dimensions of state transition matrix of the Markov model. As an example, study [17] has adopted this model for the reliability assessment of a Brazilian wind site. Literature [18] built a Markov model to jointly consider the correlation between load profile and wind power profile. The assessment result demonstrates the improvement of the Markov model.

However, the drawback of model is on the computation overhead during reliability evaluation [16,17,19,20]. In a wind farm with N WTGs and n states of wind speed, the total number of states is 2_n^N. That is, the model is not suitable to be applied to large scale system due to computing memory issues. In order to improve the model, [21] proposed a state reducing scheme in order to reduce the state number by merging the states with the same outputs.

3.1.3. Simulation model: ARMA model

In addition to Markov Model, there is another useful tool, Auto Regressive Moving Average (ARMA) model, is applicable for a reliability modeling for chorological wind power fluctuation, which is first developed by [22].

By ARMA model, the wind speed model can be defined in terms of the following variables [22]:

μ_t observed wind speed mean value at time t;
σ_t observed wind speed standard deviation at time t;
OW_t observed wind speed at time t;
SW_t simulated wind speed at time t.

and let $y_t=(OW_t-\mu_t)/\sigma_t$. Then wind speed series can be built by:

$$y_t=\Phi_1 y_{t-1}+\Phi_2 y_{t-2}+\cdots\Phi_n y_{t-n}+\alpha_t-\theta_1\alpha_{t-1}-\cdots-\theta_m\alpha_{t-m} \quad (3.3)$$

where Φ and θ represent the ARMA parameters; α is normal white noise series with zero mean value. These parameters can be determined by various methods. Numerical results in [22] have demonstrated that the difference between actual observed and simulated wind speed is quite small. Therefore the system reliability can be credibly evaluated chronologically according to the measurement of wind power or speed series.

Since the reliability assessment algorithms corresponding to Markov and ARMA model are distinguished with each other, the ARMA model is more suitable for the reliability assessment of large power systems than the Markov model. The drawbacks for ARMA model involve: (i) heavy computation overhead; (ii) relying on large amount of data for training ARMA parameters [23].

3.2. *The algorithms of reliability assessment in the planning phase of power systems*

The second step of reliability assessment is to select an appropriate assessment algorithm, which determines evaluation accuracy and computation efficiency. Many algorithms have been proposed in the last few decades and it is hence not possible to review all of them within one single paper. Therefore, we only take those algorithms into the scope of this paper, which are related to reliability assessment of wind power systems and satisfy at least one of the three conditions listed at the beginning of Section 3. These reliability assessment algorithms, which can be generally categorized as analytical and simulation methods, are comprehensively reviewed in following two sub-sections.

3.2.1. *Analytical algorithm*

There have been two main analytical methods for the reliability assessment with wind power integration. Both of them only allow that COPT or Markov model is used for wind power modeling.

The first and the most basic algorithm is the enumeration method [12,24–27], which enumerates all combinations of possible states for the entire system. The algorithm is capable of providing an accurate and direct way for reliability assessments. Although the algorithm has been widely used, it is obviously not suitable for a large-scale power system due to extremely heavy computation overhead caused by computing memory limits. When other relevant factors, e.g. wind speed correlation, exist in systems, condition probability algorithm as well as combinatorial algorithms must be introduced [14], which magnifies the computation burden.

The second analytical algorithm, i.e. the Universal Generating Function (UGF) method, is published in some literatures related to wind power [19,28,29]. The UGF method presented a clear and compact mathematical expression to the enumeration method. The main procedure for UGF are as follows [30].

For a set of discrete multi-state variables:

$$X=\{X_1,X_2,\ldots,X_M\},\quad X_i=\{X_{i1},X_{i2},\ldots,X_{in_i}\} \quad (3.4)$$

The UGF expression of them is:

$$U_{X_i}(z)=\sum_{j=1}^{j=n_i} p_{ij}z^{X_{ij}} \quad (3.5)$$

where p_{ij} is the probability of X_{ij}, z indicates z-transform is introduced.

Then let $F(X)$ denotes the “system performance function” indicating the consequence of X. Then the UGF expression of the system is written as:

$$U_X(z)=\otimes\{U_{X_1}(z),U_{X_2}(z),\ldots,U_{X_M}(z)\}=\sum_{j_1=1}^{n_1}\sum_{j_2=1}^{n_2}\cdots\sum_{j_M=1}^{n_m}P_X z^{F(X)},$$
$$P(X)=prob\{X_{1j_1},X_{2j_2},\ldots,X_{M_{j_M}}\} \quad (3.6)$$

Expected value of system is collected with the value of $U_X'(1)$, i.e. multiply the probability of each state with the corresponding evaluation result.

Generally, UGF is good at mathematically expressing enumeration method in a compact way [30]. For a specific problem, it still requires to follow the same procedure of enumeration method. Therefore, it still requires extremely high computation expense, which is not suitable for large-scale system. Interested readers are able to refer to the study of [30] which offers more detailed description and case studies.

3.2.2. *Simulation algorithm*

Comparing with enumeration methods, the simulation algorithms are more applicable for large-scale systems. These algorithms can be categorized into non-sequential and sequential simulations. Non-sequential simulation are concentrated on improving computation efficiency, and sequential simulations are concentrated on improving computation accuracy. These two types of algorithms are reviewed in the following sections.

3.2.2.1. *Non-sequential Monte Carlo simulation*

3.2.2.1.1. Crude Monte Carlo simulation. The crude MCS is known as the state sampling method, which is also a fundamental simulation algorithm for large-scale systems. The reliability indices, such as LOLP and EENS, are iteratively computed through stochastically sampling the states of the power system until the targeted indices are converged within an acceptable variance coefficient [12]. Therefore, the crude MCS method significantly reduces computation overhead by saving the enumeration of all possible states of a power system. By modeling wind power as COPT and Markov models, the method can be easily utilized for reliability assessments with wind power integration [4].

The drawback is that the crude MCS is not suitable for a system with high reliability performance. It is because the algorithm get less chance to find a failure state for a high reliability system so that the algorithms have to spend more computation expense for a converged result. Unfortunately whenever the computation time is as a limitation, the assessment result can accordingly become inaccurate.

3.2.2.1.2. Intelligent search based Monte Carlo simulation. In order to improve the sampling efficiency of crude MCS, intelligent search method was first introduced by the study [31] in 2002. The authors used the genetic algorithm (GA) as a search tool to truncate probability state space for tracking *fittest* samples. Therefore failure states, especially for a high reliability system, can be sampled efficiently. The flowchart of the algorithm is as shown in Fig. 3.2.

In Fig. 3.2, it can be observed that the sampling efficiency is improved via three approaches: (1) avoiding repeat sampling (2) tracking the most probable events (3) tracking the failure states. That is, the algorithm is able to find the most probable failure states so that a converged result can be obtained within a shorter duration.

Ref. [31] indicates that the algorithm is powerful that the computing overhead can be saved as high as 40% off comparing with that of crude MCS, and the relative error is less than 0.5%. In addition, the computation expense does vary along with reliability performances of power systems.

By adopting the intelligent search methods and the multi-state models, reliability of a wind power integrated system can be evaluated efficiently [32]. The coordination of the intelligent algorithms with MCS has been an attractive research topic for worldwide scholars. Further studies has demonstrated that various kinds of population based intelligent search methods (Ant Colony, Binary Particle Swarm, Genetic and Artificial Immune System) can be successfully applied to systems with wind power integration. It is shown in [33] that evolutionary particle swarm algorithm is even more efficient.

By studying the mechanism of the method, one can figure out that the method spends additional computation efforts on recording/searching for success states as well as evaluated states during the reliability assessment process. It can be inferred that the recording/searching effort, which is likely to be significant in large scale systems, is the shortcoming of the intelligent search method.

3.2.2.1.3. Cross-entropy based Monte Carlo simulation. The cross-entropy based MCS algorithm (CE–MCS) was proposed in [34]. The purpose of the CE–MCS method, which is to improve the efficiency of the crude MCS, is the same as the purposes of intelligent methods.

The main idea of the algorithm is to make rare events happening more frequently [34], i.e. generating more load shedding states with limited samples. The idea is realized by altering the outage probability of components, and then devoting the evaluation results obtained with distorted component parameters to their original values based on the theory of cross-entropy.

The reliability performance of Brazilian South–Southeastern generating system was used to demonstrate the effectiveness of the CE–MCS method in [34], in which one can observe tremendous efficiency improvement. Regarding wind power integrated systems, the method is considered as capable of dealing with wind power by its authors. So far the method has not been tested on any wind power related research.

Since the CE–MCS does not require additional computation efforts on recording/searching, it is more suitable to be applied to large-scale high-reliability systems than the crude MCS and the intelligent search methods. However, the accuracy of CE–MCS is dependent on the distorted outage probabilities of system components. That is, the calculation results obtained by the CE–MCS method may be inaccurate under some circumstances.

Interested readers are referred to [35] for proves or tutorials.

3.2.2.2. Sequential Monte Carlo methods. As similar as the difference between non-chorological and chorological wind models, sequential MCS methods are able to evaluate more insight reliability indices for a power system, such as frequency and duration indices of LOLF and LOLD. There are mainly two methods applicable for wind power system study: (i) original sequential Monte Carlo simulation algorithm and (ii) sequential crossing-entropy Monte Carlo simulation algorithm.

3.2.2.2.1. Original sequential Monte Carlo simulation algorithm. The original time sequential Monte Carlo simulation (TMCS) method was first proposed in [36] in 1996. The method generates chronological system statuses to obtain state residence series for each component in a system. Then the series of all the components are combined together as the system status series.

An example of the state residence time series is presented in Fig. 3.3. Considering a system consists of two generators (Unit No.1 and No.2), the state residence time series of which are shown in Fig. 3.3(a)–(b). Usually the state residence series for a component consists only two states, i.e. Available and Outage. Fig. 3.3 (c) demonstrates the series of the system, which is generated through combining the series of its components.

In contrast to the non-sequential algorithm, the ARMA model is enabled by the TMCS algorithm so that reliability assessment accuracy can be significantly improved. In some literatures, the results obtained by both applying ARMA model and TMCS is as the benchmark to examine simulation accuracy of other models or algorithms [15,23]. Additionally, the TMCS algorithm has good capabilities to cope with other time-dependent components besides wind power.

Since computation overhead is extremely high for TMCS, there have been several improved ones based on TMCS proposed by literatures [37–40]. One of those is cross-entropy based quasi-sequential Monte Carlo algorithm, which has been believed as effective and applicable for wind power system, as reviewed in the next.

3.2.2.2.2. Cross-entropy based quasi-sequential Monte Carlo algorithm. Similar to the idea of CE–MCS, the efficiency of sequential Monte Carlo simulation can be improved by distorting the

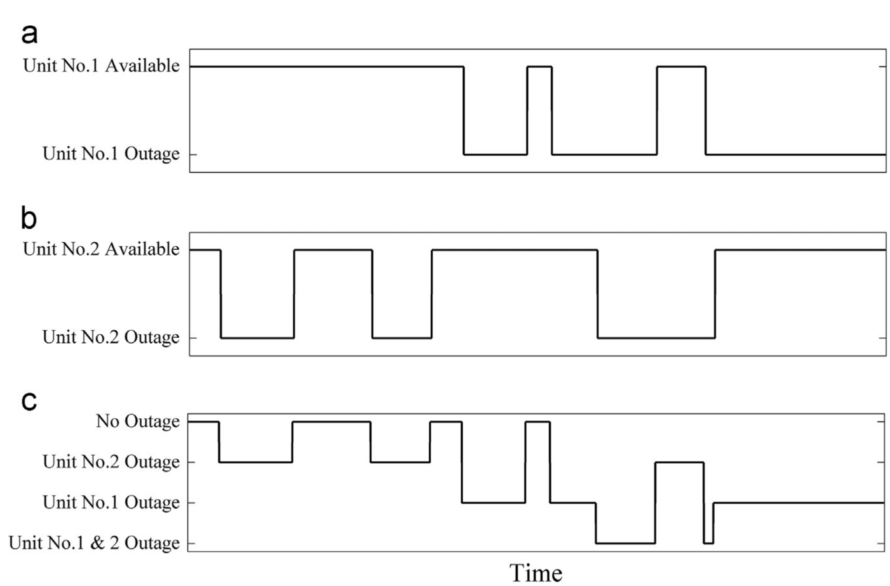

Fig. 3.3. An example to State Residence Series A comparison between distorted and original State Residence Series.

reliability parameters of system components. The CE–TMCS [38] aims at generating distorted state residence series in order to accelerate evaluations.

The main procedures of cross-entropy based quasi-sequential MCS algorithm (CE–TMCS) consists of two parts, which are (i) obtain the optimal distorted outage rates of components based on the concept of cross-entropy and (ii) evaluate the reliability of the system chronically.

The first part of the method is very similar to the one which has been explained previously. In this method, the altered parameters are the outage rates of components rather than outage probabilities. The generated state residence series of each component has two features: (i) longer "outage" time (ii) shorter "available" time, which is illustrated by Fig. 3.4.

The second part of the CE–TMCS shares the same idea as CE–MCS, which is to devote the reliability evaluation results obtained with distorted state residence series to their original values. Note that, the devotion functions of different reliability indices are distinguished from each other.

Numerical results presented in [38] have demonstrated tremendous efficiency improvements owe to the algorithm. Though this method has not been modified for reliability assessments of wind power integrated system, it is believed by the authors of CE–TMCS that the algorithm is capable to dealing with wind power as long as one specific wind power series is given. That is, applying the CE–TMCS along with ARMA wind power series can reduce the computation overhead of TMCS while reserving wind fluctuation information in maximum. Therefore the CE–TMCS algorithm is worth of further studies, especially for an actual wind power system.

3.2.3. Other algorithms

Since this paper focuses on the topic of wind integration, there are still many reliability assessment algorithms which are not included in the previous sessions since the authors did not give any discussion on algorithm capabilities once if wind power is integrated. However it does not necessarily mean that these algorithms are technically not able to deal with such cases. Some non-sequential algorithms such as latin hypercube [41], state space pruning technique [42], as well as some sequential methods such as The *pseudo-chronological* Monte Carlo simulation [37] and the *quasi-sequential* Monte Carlo simulation [38] can also be used to quantify the reliability impacts caused by wind power.

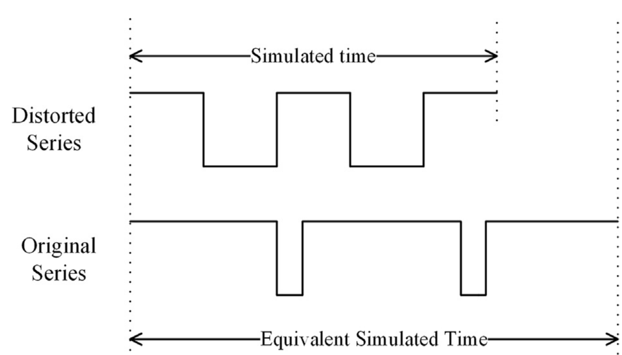

Fig. 3.4. A comparison between distorted and original State Residence Series.

Table 3.1
Elements considered in wind power capacity expansion.

	Elements	Reference
Objective function	EENS penalty	[44–48]
	Wind turbine installation cost	[44–50]
	Maintenance and operating cost	[44,45,47–49]
	Wind generation profit	[50]
	Pollutant emissions	[44,45]
Constraints	LOLP criteria	[44,50]

3.3. The applications of reliability in the planning phase of power system

3.3.1. Generation expansion planning

Generation expansion planning (GEP) is a critical optimization problem for power system planning. The goals of GEP optimization are the determinations of generation types, capacities and locations in order to meet the constantly increasing electric load while minimizing the total cost (investment and operation cost) within a range of years [43]. Since reliability performances affect system operation costs significantly, reliability consideration must be a necessary constrain of GEP optimization.

Wind capacity determination is the most important problem for the study of GEP of wind power systems. The optimization framework of the wind capacity determination are as shown in Table 3.1.

Based on the wind capacity determination problems, the allocation problems and type selection problems are further developed.

The wind farm allocation problems decides where the wind farms shall be built according to the geographically diverse wind speed profiles [49,51–53]. Geographical smoothing affections result in various investment costs as well as different reliability performances of wind power systems. By adding them as optimization variables, it is able to use the optimization framework of wind capacity determination to solve the problem of allocation selection.

The wind turbine type selection problem, which is also important in GEPs, decides which type of wind turbine should be installed at a specific wind farm. The performance of a wind farm is dependent on the types of wind turbines, among which a series of parameters are different such as hub height, cut-in, rated and cut-out speed. The differences lead to different capital costs as well as reliabilities, and then affect the overall performances of generation expansion plans. Therefore some literatures such as [49,51] recommended that the selection of wind turbines should be included in the wind power GEPs base on the wind profile of wind farms.

3.3.2. Transmission expansion planning

The increase of electric loads not only requires generation expansions but also network expansions in order to guarantee adequate transmission capacities. The transmission expansion problem (TEP) aims at figuring out the optimal paths and voltage levels (deciding capacity) during network expansion decision makings [54]. With wind power integration, transmission expansions are required in order to maintain system reliability as well as digest more wind power. The formulations of TEP optimization are quite as similar as those of GEPs.

For a wind power system, several studies are concentrated on how the reliabilities are changed due to the role changing of transmission system investments.

From the aspect of security and reliability, [11] carried out a conceptual study discussing the framework of TEPs with wind power integration, suggesting that both the deterministic $N-1$ criteria and adequacy analysis are required in the TEPs in order to carry out a thorough reliability analysis. That is, a thorough TEP study should include two part of content: (i) inspecting dynamic security performances using $N-1$ criteria and (ii) examining transmission adequacy using reliability theory.

Transmission expansion plans can be proposed by different market participators in modern deregulated power markets. Since the viewpoints of these market participators are distinguished, the performances of the transmission plans proposed by these participators are also distinguished from each other. Literature [55] pointed out that under limited investments, the transmission expansion plans proposed by wind farm owners trend to focus more on wind power digestion, while in contrast the plans proposed by TRANCOs (transmission company) focus more on reliability over long time spans.

In order to illustrate the importance of coordinated transmission expansion along with the increase of integrated wind power, [56] proposed a new reliability index to reflect the additional LOLP caused by transmission congestion. The work demonstrated possibilities of transmission overinvestments when wind generation is located in an exporting area, and possibilities of under-investments as well as significant increases in LOLP when wind power is located in an importing area.

3.3.3. *Reliability centered maintenance*

The reliability centered maintenance (RCM) is the third application of power system reliability theory. In modern power systems, the regional generation companies (GENCO), transmission companies (TRANCO) are responsible to perform scheduled maintenances in order to sustain the competitive energy market. These maintenance schedules are then reported to the local independent system operators (ISO), who will coordinates the different participators from the view of reliability of the whole system [57]. The power system reliability centered maintenance (PSRCM), which aims at working out maintenance schedules that can fulfill the maintenance requests in certain time windows while reducing the loss of load risks to minimum from the aspect of the entire system, has achieved the status of preferred maintenance practice among the modern ISOs [58].

Many efforts have been afforded to study the optimal wind turbine maintenance schedules from the view of wind farm owners according to the reliability-centered idea [59–62]. In contrast, there is very few paper referring to PSRCM from the view of grid owners or system operators. It can be explained that the power loss due one individual wind turbine is much too small to conventional generators. Therefore, it is not necessary to take them into account by ISOs in the early stage of wind development nowadays.

However, with the increase of wind penetration, we consider that the PSRCM of wind farms shall not be neglected due to two-fold reasons: (i) large-scale common-mode outages of wind farms or wind cluster can possibly occur due to lacking of maintenance schedules, which lead to significant reduction on system reliability; (ii) over maintenances will result in decrease of economic performance of both wind farms and entire power systems.

3.4. *Brief summary*

This chapter reviewed the problems of power system planning with wind power integration, as well as up-to-date wind power models and reliability algorithms which are capable of addressing with power system reliability issues due to wind power integration.

It is concluded that much research effort has been devoted to improve the accuracy and efficiency of power system reliability assessment. We categorize them as listed in Table 3.2 in order to clarify the achievements and the applications of the related research.

As can be seen Table 3.2, most of the newly developed algorithms have not been put into practice for system planning. The fact indicates that scholars shall look for more typical case systems to test and verify the effectiveness of their models and algorithms. Also, the reliability centered maintenance with wind power integration, which can be essential for future power system with higher wind penetration, are obviously lacking of focusing on from existing literatures.

4. Power system operation: Based on reliability assessment with wind power integration

The prior work in power system operation practice is to dispatch generation units, i.e. to schedule the amounts of power outputs and spinning reserves for all the units. The operation

Table 3.2
Applied planning-phase reliability models and algorithms.

Ref.	Application	Planning phase wind power reliability models			Planning phase reliability algorithms					
		Multi-state COPT	Multi-state Markov	ARMA	Analy	Simulation				
						Crude MCS	PIS	TMCS	CE–MCS	CE–TMCS
[44–46]	GEP	√			√					
[48]	GEP	√				√				
[49]	GEP	√			√					
[50,51]	GEP			√				√		
[52,53]	GEP	√			Not mentioned					
[28,29]	GEP	√			UGF					
[63,64]	TEP	√				√				
[55]	TEP			√				√		
[11]	TEP	√				√	○			
[56]	TEP	√			Not mentioned					
[65]	TEP	√			√					
[14]	Assessment	√			√					
[16,17,21]	Assessment		√		√					
[19]	Assessment	√			UGF					
[66–68]	Assessment	√			√					
[15,22,23,69]	Assessment			√				√		
[31]	Assessment		√				√			
[34]	Assessment	Not mentioned							○	
[40]	Assessment		√							√

√: Applied; ○: Recognized as capable to be applied.

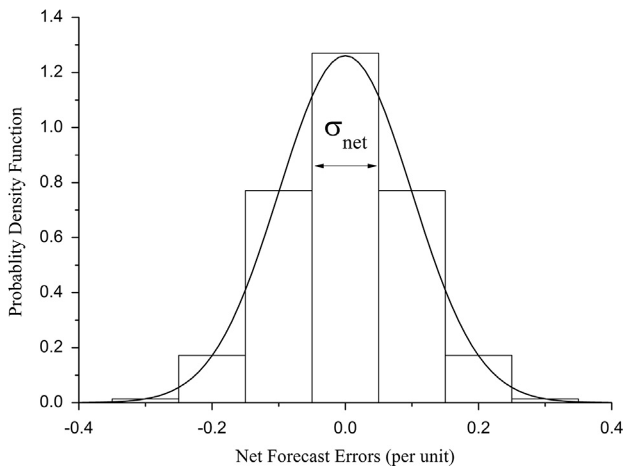

Fig. 4.1. Gaussian distribution model of wind forecasting errors.

problem studied in this section is the coordinated dispatching of wind power and conventional power.

As discussed in Section 2, deterministic methods (e.g. $N-1$) were always been implemented in conventional power systems. However these methods are no longer capable of ensuring the reliabilities of operation plans when large scale of wind power is integrated. Therefore applying reliability theory on estimating system operation risks is becoming increasingly important.

The reliability models of wind power as well as reliability assessment algorithms in the phase of operation are distinguished from those of planning phase. This is because:

(1) In the planning phase, it is impossible to forecast the fluctuation of wind power in advance of several months/years. Therefore wind power can be only modeled as a series of expectation values predicted based on historical statistics.
(2) In the operational phase, wind power can be roughly forecasted at several hours or a day ahead of dispatching. Therefore the uncertainties of wind power in the operation phase are forecasting errors, which shall be modeled and evaluated differently comparing with the methods of the planning phase.
(3) Therefore since 2003, various wind power models and corresponding algorithms have been proposed considering applications for reliability-centered system operations. Sections 4.1 and 4.2 present comprehensive reviews to the corresponding models and algorithms.

Therefore since 2003, various wind power models and corresponding algorithms have been proposed considering applications for system operations. Sections 4.1 and 4.2 would present detailed reviews to these models and algorithms.

Then in Section 4.3, the applications of reliability theory in the operation phase re introduced. A brief summary is also presented in Section 4.4 to show the gap from theories (models and algorithms) to practices (applications).

4.1. The reliability models of wind power in the phase of power system operation

In the phase of power system operation, the uncertainties of wind power are unexpected fluctuations comparing with the forecasted wind speed series, i.e. forecasting errors. In this section, two most recognized forecasting error models of wind power in the phase of operation are reviewed.

Table 4.1
Proposed reliability assessment algorithms in power system operational phase.

Forecasting error models	Reliability assessment algorithms
Normal distribution	Single stage analytical analysis
Normal distribution	Scenario tree
Normal distribution	Monte Carlo simulation
ARMA(1,1)	Scenario tree

4.1.1. Gaussian distribution model of wind power forecasting errors

Wind power forecasting errors can be modeled in a non-chronological manner by adopting Gaussian distribution, which is widely recognized according to a series of publications [70–73]. Due to the large number as well as the geographical dispersion of wind turbines, it is suitable to apply the central limit theorem in order to model the forecasting errors. Hence the forecasted errors of wind power can be modeled by zero-mean Gaussian distribution [74], which corresponds to empirical motivation [75]. Notice that the errors existed in load forecasting can be modeled as zero-mean Gaussian distribution as well. Then a net error model for wind-load forecast can be formed by merging errors of wind and load according to following formulas [70]:

$$FL_{net,t} = FL_t - FW_t \tag{4.1}$$

$$Error_{net} \sim N(\mu_{net}, \sigma_{net}), \mu_{net} = 0, \sigma_{net} = \sqrt{\sigma_w^2 + \sigma_l^2} \tag{4.2}$$

where $FL_{net,t}$ is the forecasted net load, which is obtained by subtracting forecasted value of wind power FW_t from forecasted value of loads FL_t at time t; μ_{net} refers to the mean value of the net forecasting errors $Error_{net}$; σ_{net},σ_w and σ_l indicate the standard variation of the errors of net load E_{net}, wind power and electric load, respectively.

The model introduced above is expressed as a continuous formula, which is not convenient to be considered in computation practice. Therefore it is more reasonable to consider an approximation whereby the continuous probability distribution is discretized through a number of representative samples as shown in Fig. 4.1.

The Gaussian distribution model is widely recognized by various researches. Most operational phase reliability assessment publications are based on it. However according to [76], forecasting errors of the present time is dependent on those of the previous time, meanwhile correlations of forecasting errors also exist among multiple wind farms. However the correlation features are not appropriately modeled by the Gaussian distribution model, therefore as a consequence of which the obtained reliability assessment results may be not accurate.

4.1.2. ARMA(1,1) model of wind speed forecasting errors

In contrast to the Gaussian distribution model, the ARMA(1,1) model presents a chronological description of wind power forecasting errors [77]. Comparing with the Gaussian distribution model, the advantage of this model is that the chronological as well as the geographical correlations of forecasting errors can be easily modeled.

The simplified mathematical expression of the ARMA(1,1) model is expressed as Eq. (4.3) [77]:

$$X(k) = A \times X(k-1) + C \times Z_0(k) + B \times Z(k-1) \tag{4.3}$$

where $X(k)$ and $Z(k)$ are vector with forecasting/correlation noises at hour k for N regions; A and B are diagonal matrix representing the ARMA parameters; $Z_0(k)$ indicates the independent noises at hour k; and C reflects the correlation of noises among regions.

From Eq. (4.3), we can model correlations of forecasting errors among multiple wind farms concisely by the matrix C.

As long as up-to-date wind power measurement data are available, the ARMA(1,1) model can significantly improve the quality of inner-daily dispatching of power systems since accurate forecasting errors can be computing by re-estimating the ARMA parameters.

So far, the most-recognized models for wind power uncertainties have been reviewed for power system operations. The two models are so widely accepted that they have been used in most of the literatures which study reliability-centered operations of wind power systems.

4.2. The algorithms of reliability assessment in the operation phase of power systems

With wind power integrated in power systems, reliability problems are caused by the discrepancy between the scheduled and actual wind power, i.e. as long as downward wind power fluctuation exceeds available generation, load shedding shall occur. Such discrepancy can be estimated according to several effective reliability assessment algorithms. The algorithms can be generally categorized into two groups according to corresponding forecasting error models. The model-algorithm pairs are listed in Table 4.1 as shown in the outline of Section 4.2.

4.2.1. Algorithms corresponding to normal distribution model

As we can see in Table 4.1, three algorithms have been developed for the Gaussian distribution model of wind foresting errors. These three algorithms will be reviewed respectively as follows.

4.2.1.1. Single stage analytical algorithm. The single stage analytical algorithm was proposed in Ref. [73] in order to quantify the reliability impacts caused by wind power integration under the operational phase. *Single stage* means that the algorithm aims at evaluating the reliability performance of an operation schedule at a specific time.

The main idea of this algorithm is to determine system LOLP according to the amount of reserve. By adopting the Gaussian distribution model, the probability of lacks in spinning reserve can be easily calculated. Two kinds of uncertainties are considered in this algorithms according to [73]:

(1) Unexpected net load fluctuation caused by wind power and load forecasting errors.
(2) Unexpected generation partial outages and fully outages.

Then by adding the loss of load probabilities caused by these uncertainties, the LOLP index of a specific time in power system operation can be obtained.

An example is as shown in Fig. 4.2. According to the algorithm, the net forecasting error is modeled as Gaussian distribution.

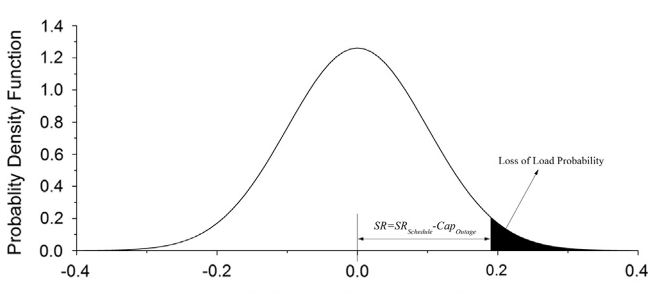

Fig. 4.2. Calculation of LOLP with Gaussian distribution model.

Positive net forecasting error values indicates that net loads are larger than expected values, under which circumstances spinning reserves (as indicated by “SR” in Fig. 4.2) are required to compensate such discrepancy. The amount of spinning reserve depends on two factors, which are the operation schedules and the unexpected outages of conventional units, and can be calculated as $\mathrm{SR} = \mathrm{SR}_{\mathrm{Schdule}} - \mathrm{Cap}_{\mathrm{Out}}$. Then the LOLP can be obtained by calculating the area of net forecasting errors exceeding the spinning reserve as indicated by “Loss of Load Probability” in Fig. 4.2.

Since the calculated LOLP is a function of the scheduled amount of spinning reserve R, then with a given threshold of LOLP, the algorithm would determine the corresponding amount of spinning reserve, which is the first step towards power system dispatching.

According to our knowledge, the single-stage analytical algorithm is the initial practical algorithm for evaluating power system reliabilities considering with wind power integration in the operation phase. The effectiveness of the algorithm is demonstrated by the study [72], which used the algorithm to examine dispatching schedules of Irish power system.

One shortcoming of this algorithm is that a number of crucial operational constraints, e.g. ramping constraints, are difficult to be considered. That might result in inaccurate assessment results so that an improved algorithm, e.g. the scenario tree algorithm, is proposed to address this issue.

4.2.1.2. Scenario tree algorithm. The scenario tree algorithm was proposed in Ref. [70]. By enumerating chronological series of net load forecasting errors, the algorithm takes the influence of sequential fluctuation of wind power into consideration so that more accurate reliability evaluation results can be obtained.

The scenario tree algorithm assumes that the net demand forecasting errors can be represented by a finite number of values, e.g. the discretized Gaussian distribution model. Then the operation plans can be made through examining a finite number of net demand forecasting error trajectories, i.e. scenarios. Each scenario is made up of sequences of *nodes* $j \in \{1, 2, \ldots, J\}$ representing one of the possible discrete realizations of the net load error. For the kth scenario, it contains the sequence of nodes of $S_k = \{j_{k1}, j_{k2}, \ldots, j_{kT}\}$, where the studied time interval is $[1, T]$. The collection of such scenarios is defined as the *scenario tree*.

Fig. 4.3 presents an example of scenario tree, in which the net load forecasting error is discretized into three levels indicated by “Low”, “As predicted” and “High”, and the studied time interval is

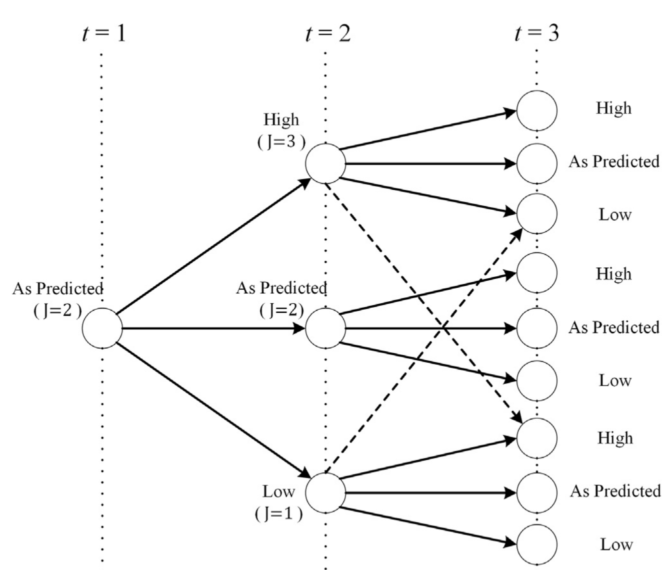

Fig. 4.3. An example of forecasting error scenario tree (ST).

[1,3]. Taking the seventh scenario as an example, the sequence of this scenario $S_7 = \{j_{71}, j_{72}, j_{73}\} = \{As\ predicted\ Low, High\}$ means that the actual wind power values are approximately treated as the equaling to, lower or higher than the forecasted values at $T=1,2,3$, respectively.

According to the statistical studies in [78], the authors of the algorithm considered that large wind power fluctuation was not rarely happening. Therefore, the forecasting errors shall be limited within a small neighborhood of the forecasted value. That is, *inter-branch* transitions, which are shown as the dashed arrows in Fig. 4.3, shall not exist in the scenario tree in order to reduce calculation burden. Finally the operation plans can be made by enumerating all the scenarios.

Notice that the ST method is still an enumeration-based method. Therefore the main drawback of the algorithm is the computation overhead caused by scenario enumerations. The number of scenarios grows exponentially along with the number of stages resulting in quite heavy computation overheads.

4.2.1.3. Monte Carlo simulation. In order to reduce the calculation burden of scenario tree algorithm, the Monte Carlo simulation algorithm was proposed in Ref. [71]. The Monte Carlo algorithm generates net forecasting errors according to a Gaussian cumulative probability distribution function, which can be written as Eq. (4.4) [71]:

$$\varepsilon_t = \sqrt{2}\sigma_{net} erf^{-1}(2z_t - 1) \tag{4.4}$$

where ε_t is the net demand forecasting error at time t; z_t is a random number uniformly distributed over the interval [0,1]; and erf^{-1} indicates the inverse error function. The generated forecasting error series, which are determined by a series of random series z_t, can be used to examine the reliability of daily operation schedules.

As similar as the crude MCS algorithm introduced in Section 3, the MCS algorithm is capable of improving the efficiency of reliability assessments via iteratively generated series of forecasting errors. In [80], the authors applied the algorithm on determining the spinning reserve adequacy of the Portuguese power system, which partially demonstrates that the effectiveness of this algorithm.

The shortcoming of the method is as similar as discussed in Section 3. That is, the Monte Carlo simulation algorithm also encounters the similar efficiency problem of high-reliability systems: very high computation efforts are used for evaluating non-failure system states and the algorithm takes very long time to satisfy converging criteria.

The three algorithms reviewed above can be used along with the Gaussian distribution model. The algorithms corresponding to the ARMA(1,1) are introduced in Section 4.2.2.

4.2.2. Algorithms corresponding to ARMA model: Scenario tree

As discussed in Section 4.1, the ARMA(1,1) model is able to presenting a more accurate description of wind power forecasting error comparing the Gaussian distribution model by considering geographical and chronological dependency of the errors. Various works have been devoted to develop reliability assessment algorithms corresponding to the ARMA(1,1) model.

The most-recognized algorithm based on the ARMA model is the Scenario Tree (ARMA-ST) algorithm, which was introduced in [81]. By adopting the wind power forecasting error model of ARMA(1,1), ARMA-ST algorithm is expected to obtain more accurate reliability assessment results comparing with the previous scenario tree algorithm corresponding to the Gaussian distribution model.

The scenarios of ARMA-ST are generated through a different method, which is based on the probabilities of series and the Euclidean distances between each other. An example given in [82] is shown in Fig. 4.4 in order to illustrate the procedure of this method. The following steps represent how 10 original scenarios can be used to build up an 8-scenario tree of three-stage.

(1) Generate a large number of original series based on the ARMA (1,1) model. In Fig. 4.4, 10 scenarios are generated as shown in the figure titled with "Step 1".
(2) In order to reduce the redundant 10 scenarios to 2^T scenarios, where T indicates the state number, two original series shall be removed. As can be observed in step (1), the original series of S3 and S4 are relatively closed to S9. Then S3 and S4 are

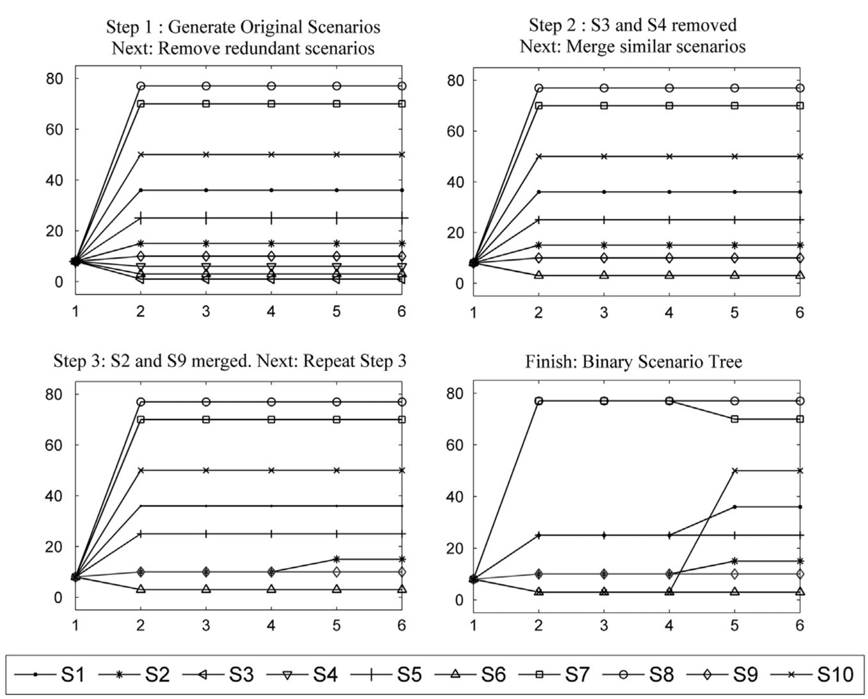

Fig. 4.4. An example of establishing a binary scenario tree with ARMA(1,1) model.

removed since their probabilities are less than the probability of S9, as shown in the figure titled with "Step 2".

(3) Now the remaining 8 series shall be merged into a three-stage manner. It can be observed that in the second figure S2 and S9 are close to each other. Therefore, as shown in the third figure, part of S2 is merged into S9 if the probability of S2 is smaller.

(4) By repeating the step (3), the three-stage 8-scenario tree can be obtained. Notice that the distance from S2 and S6 is large which indicates the two series shall not be merged. That is because since the other scenarios, i.e. S7 and S8, S1 and S5, S2 and S9, have already been merged together, and S2 and S6 are the only two left for merging. Finally without any other option, the binary tree is established by merging S2 and S6 together.

In addition to the advantages of the ARMA(1,1) forecasting error model, the ARMA-ST algorithm is with two advantages. By procedure (1), information about forecasting errors is generated according to original measurement series; and by (2), redundant information is reduced so that the algorithm can be computed efficiently. Eventually the most representative information are selected in the 2^T scenarios, the number of which is significant reduced comparing with that of the STT algorithm based on Gaussian distribution model.

With the ARMA-ST tool, the idea of *Rolling Planning* was proposed in [83], suggesting system operators to re-schedule the dispatching plans every 3 h or so. Since the ARMA(1,1) model gives better estimation of the forecasting errors while new data is available, the scenario tree can be re-generated and the operation plans can be corrected accordingly in time.

In [84], a simplified ARMA scenario tree algorithm was proposed aiming at reducing the number of scenarios, which is realized by limiting the number of nodes allowed to grow separated branches. As a result, the number of scenarios is reduced to hundreds rather than millions.

4.3. The applications of reliability in the operation phase of power systems

With considering of wind power integration, the operational-phase problems discussed in this paper involve *unit commitment*, *economic dispatch* problems, which are investigated from different aspects as listed in Table 4.2.

The reliability performances of UC and ED schedules are challenged by uncertainties of wind power, and so far the only practical way to compensate unexpected wind power fluctuation is to use the spinning reserve provided by conventional units. That is, the reliability performances of UC and ED schedules are dependent on very similar crucial issue, i.e. the amount of spinning reserve.

The amounts of spinning reserve can be decided through deterministic criteria, such as a certain percent of the hourly-load, or capacity of the largest online unit ($N-1$ criteria). Even a set of deterministic criteria have been comprehensively formulated, they may still result in inconsistent decisions and variable operating risks, especially when variable wind power is integrated. Under such circumstances, the concept of power system reliability, which is originally designed for long term applications, can be smoothly applied on UC and dispatching problems with variable wind power integration.

The amount of spinning reserve is usually determined through a two-step sequence.

(i) The amount of SR is roughly determined at a day ahead of market clearing by studying UC problems with estimated forecasting errors.

(ii) The amount of SR is determined again at few hours ahead of market clearing by studying ED problems with updated forecasting errors.

In our opinion, all the algorithms reviewed in Section 4.2 can successfully estimate a suitable amount of spinning reserve at unit commitment stages. However at stages of daily re-dispatch, refined wind power measurements would suggest major re-estimations of wind power forecasting errors are necessary, thus the ARMA(1,1) model along with the ARMA Scenario Tree algorithm and the concept of rolling-planning seems to be a more comprehensive choice.

4.4. Brief summary

Reliability has become an essential consideration and constraint for system secure operations with wind power integration. Wind power forecasting error models and corresponding reliability assessment algorithms are reviewed in this section. The applications of the reviewed models and algorithms are listed in Table 4.3.

5. Conclusion

In this paper, we reviewed the problems of reliability-based power system planning and operation with wind power. It can be demonstrated that reliability theory is becoming increasingly important after wind power introduces great uncertainties in the planning and operation stages of power systems. This paper reviews various reliability models of wind power as well as reliability assessment algorithms, and some interesting phenomenon can be observed.

Regarding planning phase reliability assessment, three reliability models of wind power are reviewed in this paper, i.e. the Multi-state COPT, the Multi-State Markov and the ARMA model, and the Multi-state COPT model is the most popular one in applications, despite its low accuracy on modeling the time/geographical correlations of wind speed profiles. This phenomena is worthy of paying attention to since the correlation effects, wake effects and so on would have significant impacts on reliability assessment results. Many advanced reliability assessment algorithms such as intelligent-search and cross-entropy based algorithms have been proposed in recent years. However they have not been implemented in applications yet. The fact indicates that scholars shall look for more typical case systems to test and verify the effectiveness of their algorithms. Generation/transmission expansion problems with wind energy have been studied in

Table 4.2
Applications of power system reliability theory in wind power operations.

Problems	Definitions	Time scale
Unit commitment (UC)	Scheduling the switching of generators at a day ahead of actual generation	Inter-day
Economic dispatch (ED) (Also: daily re-dispatch)	Determining the most economic output combination of generators with given generator statuses and amount of electric loads	Inter-hours

Table 4.3
Applied operational-phase reliability models and algorithms.

Ref.	Uncertainty models		Reliability assessment algorithms		
	Normal distribution	ARMA(1,1)	Analytical	STT	MCS
[72,73]	√		√		
[70,79]	√			√	
[71,85]	√				√
[81,83,84]		√		√	
[86,87]: Models without considering any forecasting errors					

various literatures. However the topic of reliability-centered-maintenance with wind power integration is only studied at the scale of a single wind turbine generator, and we consider it is also important to investigate the problem from the aspect of power system.

Regarding operation phase reliability assessment, reliability consideration has become an increasingly important issue in operational decision makings such as unit commitment or economic dispatch problems with wind energy. We would like to emphasize the point again that the uncertainties in the phases of planning and operation are obviously distinguished and shall be considered with different models and algorithms.

Acknowledgement

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