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RELIABILITY ASSESSMENT FOR WIND TURBINES CONSIDERING THE INFLUENCE OF WIND SPEED USING BAYESIAN NETWORK

OCENA NIEZAWODNOŚCI TURBIN WIATROWYCH ZA POMOCĄ SIECI BAYESA Z UWZGLĘDNIENIEM WPŁYWU PRĘDKOŚCI WIATRU

The reliability of wind turbine is of great importance for the availability and economical efficiency of wind power system. In this article, a reliability model for wind turbine is built with Bayesian network (BN), in which the influence of wind speed is considered. Causal logic method (CLM) is presented for qualitative modeling, which combines the merits of fault tree in handling technical aspects and the strength of BN in dealing with environmental factors and uncertainty. A novel adjustment method based on expectation is proposed for quantitative calculation, by which historical data and expert judgment are integrated to describe the uncertainty in the prior probability distributions. An approximate inference algorithm combining with dynamic discretization of continuous variables is adopted to obtain the reliability index of wind turbine and its elements. A case study is given to illustrate the proposed method, and the results indicate that wind speed is an important factor for the reliability of wind turbine.

Keywords*: Bayesian network, wind turbine, reliability assessment, wind speed.*

Niezawodność turbiny wiatrowej ma ogromne znaczenie dla gotowości i efektywności ekonomicznej instalacji wiatrowej. W niniejszym artykule zbudowano, w oparciu o sieci Bayesa (BN), model niezawodności turbiny wiatrowej uwzględniający wpływ prędkości wiatru. Przedstawiono Metodę Logiki Przyczynowości (Causal Logic Method, CLM), służącą do modelowania jakościowego, która łączy zalety drzewa błędów w odniesieniu do aspektów technicznych z atutami BN w odniesieniu do czynników środowiskowych i niepewności. Do kalkulacji ilościowych zaproponowano nową metodę dopasowania opartą na oczekiwaniach, w której dane z eksploatacji i opinie ekspertów łącznie pozwalają opisać niepewność rozkładów prawdopodobieństwa a priori. Wskaźnik niezawodności turbiny wiatrowej i jej elementów otrzymano posługując się algorytmem wnioskowania przybliżonego w połączeniu z dynamiczną dyskretyzacją zmiennych ciągłych. Dla zilustrowania proponowanej metody przedstawiono studium przypadku, którego wyniki wskazują, że prędkość wiatru jest ważnym czynnikiem niezawodności turbiny wiatrowej.

Słowa kluczowe*: Sieć Bayesa, turbina wiatrowa, ocena niezawodności, szybkość wiatru*

1. Introduction

Wind energy is a kind of clean and renewable energy. Its installed capacity has grown rapidly around the world in recent years [7]. In China, for instance, it has shown a booming growth in wind power since 2005, and the installed capacity has increased from 503MW in 2005 to around 60GM by the end of 2012 [14]. Due to the variability of wind, shifting loads and fluctuating energy demands, components of wind turbines are susceptible to damage, including gearboxes, blades, generators and electrical components, etc [13]. Since wind power projects are long-term and capital-intensive, spanning about 20–25 years, the failures of components will cause excess repair and maintenance costs, thereby reducing the power generation [12]. For instance, for a variety of reasons, the average utilization time of wind turbines with full capacity in China is only 1920 hours in 2011, which is significantly lower than 2200 hours as planned.

With the increasing number of wind turbines and wind farms, the importance of their reliability and availability has attracted great attention. Negra et al. [20] summarized the factors that affect the reliability of wind power system, including wind turbine performance, and some reliability evaluation indices were also presented. Considering wind turbine as a two-state system, Manco et al. [16] proposed a reliability model with Markovian approach. Fazio et al. [8] adopted universal generating function (UGF) to build the reliability model of wind turbine, in which wind speed, energy conversion and failure characteristics were considered. Guo et al. [10] applied three-parameter Weibull distribution to describe the reliability growth of wind turbines with incomplete failure data. But up to now, the research on reliability assessment for wind turbines is still very limited [9].

Wind turbine is a kind of multi-component complicated system. The behaviors of the components in such a system include failure priority, dependent failures and interactions, etc [15]. In practice, the interactions among the assemblies of wind turbines are quite complicated, thus it can not simply be regarded as a series blocks of assemblies [2]. Furthermore, the reliability of wind turbine is also affected by various environmental factors, such as wind speed, temperature, humidity, location of wind farm [30]. By analyzing failure data and wind speed data, Tavner et al. [27] concluded that high wind speeds reduce wind turbine reliability. Su et al. [25] analyzed the correlation between failure rate of wind turbine and wind speed by time series approach. They ascribed a periodicity in failure rates of wind turbines to the effect of wind speed, but didn't go further to investigate how to take wind speed into consideration when evaluating the reliability. The interaction among the components and the influence of wind speed greatly increase the difficulties in system reliability assessment with traditional reliability methods.

Bayesian network (BN) has the ability to depict the uncertainty and interactions among the assemblies. It also provides the possibility to combine different sources of information together, such as expert knowledge, environmental and human factors. Most associated literatures focused on the learning and inference algorithms related with BN. Nonetheless, the application of BN in reliability has aroused great interest among researchers in the past few years [28]. Bobbio et al [3] showed how to map fault trees into BN, and reliability analysis for a multiprocessor system was also completed with BN. Compared with fault tree method, some restrictive assumptions in BN can be removed, and various dependencies among components can also be expressed efficiently. Marquez et al. [17] proposed a hybrid BN framework to analyze dynamic fault tree, meanwhile, the failure distributions of static and dynamic logic gates were obtained by using an approximate inference algorithm involving dynamic discretization of continuous variables. Boudali et al. [5] presented a discrete-time BN framework to fulfill the reliability analysis for a dynamic system. They also proposed a continuous BN framework, which considered not only the combination of failure events, but also the sequence ordering of the failure [4]. Sørensen [23] described the degradation process before failure by pre-posterior Bayesian, and the influence of uncertainty on degradation, maintenance cost and whole life cycle cost were analyzed in order to optimize the operation and maintenance.

In this paper, BN is adopted to build reliability model of wind turbine, and wind speed and the uncertainty in reliability parameters are also taken into consideration. A casual logic method (CLM) is proposed to build the qualitative model, and a novel method is presented to handle the uncertainty of parameters. The case study indicated that by considering the influence of wind speed, the reliability assessment results of wind turbine are more practical.

The remainder of this paper is organized as follows. Section 2 gives a brief introduction of BN, and the procedure to build a reliability model based on BN is also provided. CLM for qualitative modeling is presented in Section 3. In Section 4, a novel adjustment method based on expectation is proposed to adjust prior probability distribution, and an approximate inference algorithm combining with dynamic discretization is adopted to obtain conditional probability distributions. In Section 5, a case study for wind turbine reliability assessment considering the influence of wind speed is provided to illustrate the feasibility of the proposed approach. In Section 6, conclusions and further studies are offered.

2. Reliability modeling based on Bayesian network

2.1. Introduction to Bayesian network

Bayesian network (BN) is also known as casual network, or probabilistic dependence graph [3]. It is a graphical network established on the basis of well-defined probabilistic reasoning, and it has strong ability to deal with uncertainty and dependence [6]. Based on the observations and other prior information, the probability distribution of random variables can be calculated by BN.

In general, the definition of a BN can be divided into two parts: qualitative and quantitative [18]. The qualitative part is described by a directed acyclic graph (DAG), in which the nodes represent system variables $X=\{x_1, x_2, \dots, x_n\}$, and directed arcs symbolize the causal or influential relationships between variables. Fig. 1 gives a simple BN with nodes $\{x_1, x_2, x_3, x_4\}$, in which only the qualitative part is shown. Nodes x_1 and x_2 are the parents of node x_3, and node x_3 is the parent of node x_4. The direct arcs between nodes x_1 and x_3 as well as nodes x_2 and x_3 mean that node x_3 is affected by nodes x_1 and x_2, while x_1 and x_2 are independent. Similarly, node x_4 is dependent on node x_3. The quantitative part is conditional probability distributions (CPD), $p(x_i|\text{pa}(x_i))$, which define the probability relationship among the nodes by their parent nodes $\text{pa}(x_i)$. Those nodes without parents are called root nodes, and their CPD can be simply indicated as $p(x_i|\phi)=\text{p}(x_i)$, which is also called prior probability distributions. The main feature of BN is representing a joint probability distribution by factorization of variables based on conditional independence, which can be expressed as

$$p(x_1, x_2, \dots, x_n) = \prod_{i=1}^{n} p(x_i \mid pa(x_i)) \quad (1)$$

According to the separation of conditional independence, the distribution of joint probability can be divided into some simple probability distributions. In this way, the complexity of the model is reduced, and the inference efficiency can be improved obviously. Take Fig. 1 as an example, its joint probability distribution is equivalent to

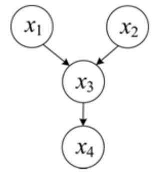

Fig. 1. An example BN with nodes $\{x_1, x_2, x_3, x_4\}$

$$p(x_1, x_2, x_3, x_4) = p(x_1)p(x_2)p(x_3 \mid x_1, x_2)p(x_4 \mid x_3) \quad (1a)$$

The marginal probability distribution of a node can be obtained by joint probability distribution. Assuming that the nodes in Fig. 1 are discrete, the marginal probability distribution of x_4 is denoted as

$$p(x_4) = \sum_{x_1, x_2, x_3} p(x_1, x_2, x_3, x_4) = \sum_{x_1, x_2, x_3} p(x_1)p(x_2)p(x_3 \mid x_1, x_2)p(x_4 | x_3) \quad (1b)$$

2.2. Modeling process

In this study, we are interested in the reliability assessment of wind turbines based on BN, and the influence of wind speed is also considered. Roughly, there are four steps involved in the modeling, as seen in Fig. 2.

Step 1: **System definition.** Basic events and logic gates are determined by classical reliability analysis methods, including FTA and RBD. Afterwards the environmental factors, such as wind speed, are introduced into the model on the basis of the requirement of reliability assessment. Meanwhile, continuous and discrete variables are also defined at this stage.

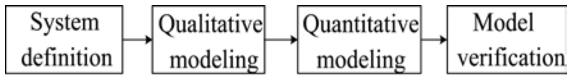

Fig. 2. Flow chart of reliability assessment

Step 2: **Qualitative modeling.** CLM is adopted to establish qualitative model, i.e., definition of DAG. In order to make the inference effective, intermediate nodes are necessary when a node has more than three parents.

Step 3: **Quantitative modeling.** It includes the setting of prior probability distributions and CPD. Prior probability distributions are obtained based on historical data and subjective judgment. The root nodes which correspond to the assemblies or subsystems of wind turbine are characterized by their prior probability density functions. A novel approach is proposed to adjust the parameters of prior distributions. All non-root nodes, i.e. logic gates and dependent components, are characterized by their CPD.

Step 4: **Model verification.** Reliability evaluation and sensitivity analysis are included in this step. In this article, an approximate inference algorithm combining with dynamic discretization of continuous variables is adopted to obtain TTF distribution of wind turbine. The details can be found in Ref. [21]. The result is also compared with the one that doesn't consider the influence of wind speed and the uncertainty of parameters. Sensitivity analysis is conducted to illustrate how the reliability of wind turbine changes with the variations of average wind speed.

3. Qualitative modeling

Ref. [22] presented a hybrid causal logic method (HCLM), in which BN was integrated into event sequence diagrams or fault trees. Inspired by HCLM, we present a casual logic method (CLM) to guide the reliability modeling of wind turbine based on BN. Firstly the logic relation of fault tree is transformed into BN, then wind speed is added into BN regarded as a common environmental factor. Finally, the BN model is adjusted again for considering the uncertainty of parameters in prior probability distribution. Compared with HCLM, CLM guarantees that all the basic events are represented only once, which can reduce the complexity of the model. Meanwhile, a new algorithm of combination of fault trees and BNs is dispensable. An example is showed in Fig. 3 to illustrate CLM in detail.

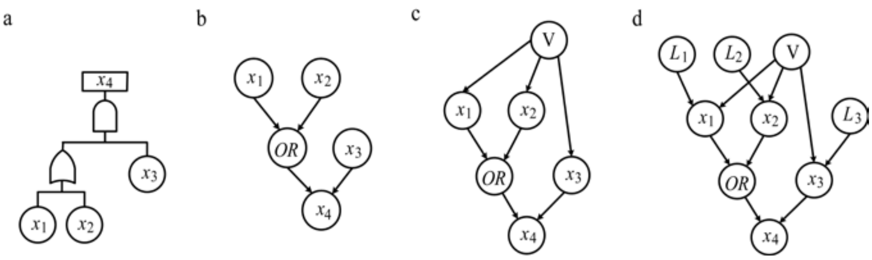

Fig. 3. CLM framework: a) Fault trees of an example; b) Mapping fault trees to BN; c) Components affected by wind speed; d) Uncertainty of prior probability distributions.

As seen in Fig. 3a, it is assumed that a fault tree of wind turbine consists of three basic events x_1, x_2, x_3 with an AND gate and an OR gate respectively. Either event x_1 or x_2 failure will lead to the failure of OR gate's output. As for AND gate, top event x_4 fails only when all of its input events fail. Therefore, the cut sets are $\{x_1, x_3\}$, $\{x_2, x_3\}$, and $\{x_1, x_2, x_3\}$, which are used for defining all the fault modes of the system. The fault tree can be mapped into BN, shown as Fig. 3b. The basic events in fault tree equal to the root nodes in BN. It needs to be pointed out that if the basic events appear more than once, one corresponding node in BN is enough. Similarly, each logic gate can be represented by a corresponding node in BN. Nodes are connected by directed arcs in BN just as corresponding gates in fault tree.

In practical applications, the reliability of wind turbine is also affected by wind speed, which is difficult to be handled quantitatively. In this paper, the influence of wind speed is expressed by the change of components' life-lengths. When wind speed is not taken into consideration, the life-lengths of components are independent. But when components are exposed to some common environment, the correlation among their life-lengths is as follows: a tough environment leads to reduced life-lengths for all components, whereas a gentle environment implies that the life-lengths of the components are increased. Thus, let V represent wind speed, and make links between node V and each component to express the influence of wind speed on them. The qualitative part of BN model considering wind speed influence is built, as illustrated in Fig. 3c.

Furthermore, the uncertainty of parameters is also considered in the BN model. In general, the TTF distributions of basic events are assumed to be probability distributions with constant parameters. But in this study, parameters are considered as random variables, and modeled using probability distributions. Nodes L_1, L_2, L_3 are created to describe the probability distribution of parameters, and are added as the parents of corresponding nodes, as shown in Fig. 3d.

The qualitative reliability model with BN can be built according to the steps above. The corresponding BN model can describe the structure of wind turbine, the interactions among components, and the influence of environmental factors on system reliability.

4. Quantitative calculation

In this study, continuous nodes are used to represent TTF of basic events and logic gates, and discrete nodes are used to describe the states of wind turbine and its subsystems at a particular point in time. Prior probability distributions and CPD are needed to evaluate wind turbine reliability. If sufficient historical data are available, prior probability distributions can be obtained. But in practice, failure data are usually limited. Therefore, the prior probability distributions are usually obtained according to the judgment of experts' knowledge and experience. A novel approach is proposed in Section 4.2 to adjust parameters of prior probability distributions, which can combine historical data and expert judgment. CPD for TTF τ of fault tree logic gates, $f(t|\mathrm{pa}(\tau))$, needs to be calculated, where τ is a function of corresponding input components' TTF, namely $\tau = \rho(\mathrm{pa}(\tau))$.

Considering the reliability model consists of both discrete and continuous nodes, and after adjustment the prior probability distributions are non-Gaussian distributions, an approximate inference algorithm combining with dynamic discretization of all continuous variables are adopted to generate TTF distributions of wind turbine and its subsystems. Thus the reliability of wind turbine at any mission time can be derived.

4.1. Dynamic discretization and approximate inference

Inference is carried out using a standard BN propagation algorithm. Considering the reliability model of wind turbine includes both discrete and continuous nodes with non-Gaussian distributions, exact inference seems troublesome. An approach is applied in this paper, by which the ranges of all continuous variables are dynamically discretized, and CPD at each discretization step is approximated by using a weighted uniform density function [21].

The dynamic discretization consists of two parts: 1) searching an optimal partition set $\Psi=\{w_1, w_2, \ldots, w_n\}$ in range of variables; 2) optimizing the values for the discretized probability density function $\tilde{f}(t)$, which are defined as a piecewise constant function on the partitioning intervals.

Different from the static discretization splitting the range evenly, the dynamic discretization searches the variable range for most accurate specification of high-density regions. At each stage in the iterative process, a candidate discretization, $\Psi=\{w_1, w_2, \ldots, w_n\}$, is judged whether the entropy error is below a given threshold. If not, repeat the process until at an acceptable degree.

The approximate inference algorithm uses a weighted uniform density function to approximate the conditional density functions after each dynamic discretization. Here is a case with only two parents to illustrate the approximate inference algorithm:

1) Assume system S has two parent nodes A and B. The TTF of S, A, B are t_A, t_B, t_S, respectively. t_S can be expressed by its input nodes, namely $t_S=\rho(t_A, t_B)$.
2) Suppose the variables have partition sets Ψ_A, Ψ_B. For each pair of interval in the respective sets Ψ_A and Ψ_B, such as an interval (a_1, a_2) in Ψ_A and (b_1, b_2) in Ψ_B, the maximum m and minimum l for each set of values $\rho(a_1, b_1)$, $\rho(a_1, b_2)$, $\rho(a_2, b_1)$, $\rho(a_2, b_2)$ are calculated with the approach respectively.
3) If the number of such kind of interval is I, then a uniform probability density mass $U(l_i, m_i)$ is generated in interval (l_i, m_i) over the range of t_S, for $i \in$ I. Assuming that partition set $\Psi s=\{w_1, w_2, \dots, w_n\}$, then the conditional density function of nodes t_S in the partitioning interval w_k can be defined as

$$p(t_S \in w_k)U(t; l_i, m_i) \tag{2}$$

where $p(t_S \in w_k)$ represents the fraction of uniform mass $U(t; l_i, m_i)$ corresponding to the interval w_k

$$p(t_S \in w_k) = \begin{cases} \int_{w_k} U(t; l_i, u_i)dt & \text{if} \quad w_k \cap (l_i, m_i) \neq \phi \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

By iteratively updating the partitioning intervals using dynamic discretization, the accurate approximations of CPD are obtained, and the input variables are not limited to exponential or Gaussian families.

4.2. Parameter uncertainty of prior probability distribution

In this section, a novel method called adjustment method based on expectation is proposed to deal with the uncertainty of parameters in prior probability distributions. Generally, the expected values of TTF distributions can show the average life-lengths of components. It is simple and intuitive to judge the fluctuating ranges of average life lengths, while it is hard to decide the parameters of the distribution functions. Therefore, the expected values of TTF distributions together with regulation factors are considered to achieve uncertainty of prior probability distributions.

Suppose the TTF distribution of a node in BN is f with parameters $K=\{K_1, K_2, \dots, K_n\}$, i=1, 2, …, n, which can be expressed as $f(t|K_1, K_2, \dots, K_n)$ with $t \geq 0$. Its expectation can be calculated by

$$ET = \int t \cdot f(t|K_1, K_2, \dots K_n)dt = g(K_1, K_2, \dots K_n) \tag{4}$$

Now the parameters $K=\{K_1, K_2, \dots, K_n\}$ are obtained based on historical data, namely $K_1=k_1, K_2=k_2, \dots, K_n=k_n$. The distribution with constant parameters can be written as $f(t|K_1=k_1, K_2=k_2, \dots, K_n=k_n)$, and its expected value can be calculated by Eq. (4)

$$E(t|K_1 = k_1, K_2 = k_2, \dots, K_n = k_n) = g(k_1, k_2, \dots, k_n), \tag{5}$$

Let the regulation factors of parameters $K=\{K_1, K_2, \dots, K_n\}$ be $\theta=\{\theta_1, \theta_2, \dots, \theta_n\}$, i=1, 2, …, n. The uncertainty of parameter K_i is dependent on regulation factors θ_i, which belongs to [0, 1]. The bigger θ_i is, the less convincible fitting distributions will be. Here, we assume that the expectation obeys triangular distribution as below after expert's adjustment.

$$g(k_1, k_2, \dots, K_i, \dots, k_n) \sim Triangle((1-\theta_i)g, (1+\theta_i)g, g), \tag{6}$$

where g is short for the expected value $g(k_1, k_2, \dots, k_n)$ in Eq. (5); $(1-\theta_i)g$ and $(1+\theta_i)g$ represent the lower limit and upper limit of triangular distribution, respectively.

The distribution for parameters can be generated from Eq. (6), shown as

$$K_i \sim \text{triangular}\,(\min(g^{-1}((1-\theta_i)g), g^{-1}((1+\theta_i)g)), \max(g^{-1}((1-\theta_i)g), g^{-1}((1+\theta_i)g)), g^{-1}(g)), \tag{7}$$

where g^{-1} is the inverse function of $g(k_1, k_2, \dots, K_i, \dots, k_n)$ in Eq. (6).

Here is an example to illustrate the method. Suppose the TTF distribution of component A is exponential distribution with $k=1/1000$, i.e. Exp(1/1000). The regulation factor given by expert is 0.2, then we can obtain that $k \sim$ triangular (1/1200, 1/800, 1/1000) according to Eqs. (4) – (7). The prior probability distribution of component A after adjustment is shown as Fig. 4:

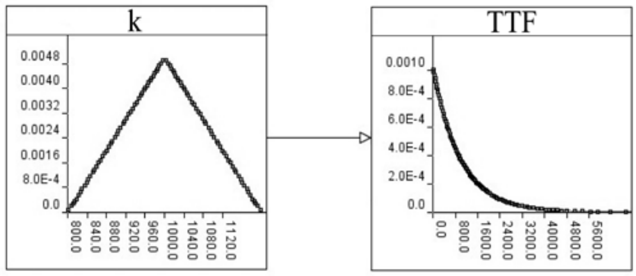

Fig. 4. An example for adjustment of prior probability distribution

4.3. CPD for Boolean constructs

The dynamic discretization algorithm, together with the approximation approach, allows us to estimate the CPD for the fault tree constructs automatically.

The TTF of Boolean constructs in simple fault trees are defined by the input components of the construct, i.e., $\tau=g(pa(\tau))$. Let t_i (i=1, 2, …, n) denote the TTF of the ith parent node.

The AND gate means that only if all the input components fail, the output of the AND gate will fail. Suppose TTF of AND gate is t_{AND}, and according to the definition of AND gate, its failure probability in time interval (0, t] can be given by

$$p(t_{\text{AND}} \leq t) = p(t_1 \leq t, \cdots, t_n \leq t) = p(\max_i \{t_i\} \leq t), \tag{8}$$

where the TTF of AND gate, t_{AND}, is a random variable defined by its corresponding input nodes' TTF, namely $t_{\text{AND}} = \max_i \{t_i\}$.

As for OR gate, it means that if at least one input component fails, the output of the OR gate will fail. Similarly, the failure probability of t_{OR}, namely the TTF of OR gate, in time interval (0, t] can be formulated as

$$p(t_{\text{OR}} \leq t) = 1 - p(t_1 > t, \cdots, t_n > t) = p(\min_i \{t_i\} \leq t) \tag{9}$$

where the TTF of OR gate t_{OR} is a random variable defined by its parents, namely $t_{OR} = \min_i \{t_i\}$.

5. Case study

5.1. Description of wind turbine

Wind turbine is a complicated system which is composed of several subassemblies. Fig. 5 shows the main subassemblies in a typical geared generator wind turbine [1]. Although all the subassemblies are indispensable both in function and reliability, for simplification here we only focus on some important subassemblies, including gearbox, blades, generator, electrical subsystem, converter, yaw assembly, pitch assembly, brake assembly, and hydraulic assembly. Brake assembly is parallel connected by air brake and mechanical brake. From the view of reliability, the above assemblies can be considered in series, and the reliability block diagram is shown in Fig. 6. Safety subsystem is composed of yaw assembly, pitch assembly, brake assembly, and hydraulic assembly. It is of great importance for the operation, reliability and safety of wind turbine. Fig. 7 illustrates a fault tree, in which the basic events represent the failure of subsystems or assemblies, and the failure of wind turbine is the top event. The symbols for the basic events are shown in Table 1.

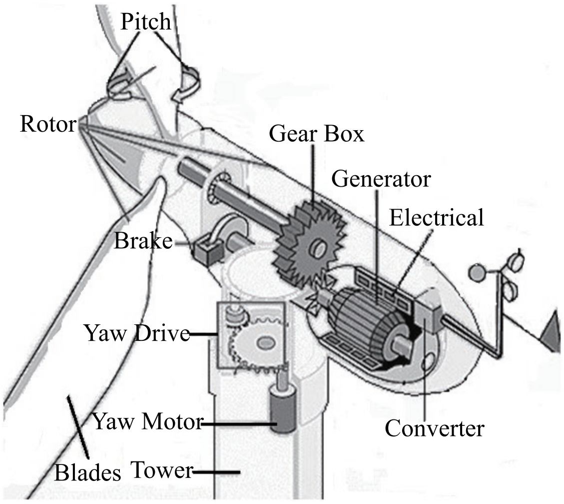

Fig.5. Structure of wind turbine

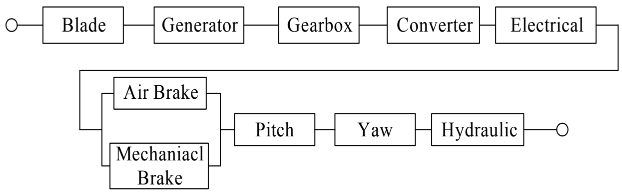

Fig. 6. Reliability block diagram of wind turbine

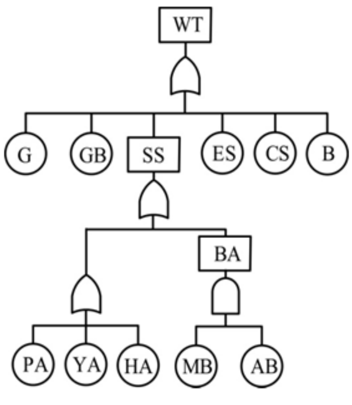

Fig. 7. A fault tree of wind turbine

Table 1. Symbols for basic events

Symbol	Basic event
G	Failure of Generator
GB	Failure of Gear Box
B	Failure of Blade
ES	Failure of Electrical Subsystem
CS	Failure of Converter Subsystem
SS	Failure of Safety Subsystem
PA	Failure of Pitch Assembly
BA	Failure of Brake Assembly
HA	Failure of Hydraulic Assembly
YA	Failure of Yaw Assembly
AB	Failure of Air Brake
MB	Failure of Mechanical Brake

Generally, the wind turbine could continue to work when safety subsystem fails, but in a suboptimal situation [1]. Therefore, it's not always practical to consider safety subsystem as a series relationship. Considering that classical reliability methods are not skillful in dealing with the environmental factor, in this article BN is applied to build the reliability model, and study the influence of wind speed on the reliability.

5.2. Reliability model of wind turbine based on BN

5.2.1. Qualitative modeling for reliability of wind turbine based on BN

On the basis of fault tree in Fig. 7 and the function of safety subsystem, the BN model which ignores the safety subsystem is built, as show in Fig. 8a. The corresponding BN model of the safety subsystem is as shown in Fig. 8b. The influence of safety subsystem on wind turbine reliability is mainly reflected on the protection of blades. The life-lengths of blades are affected by the state of safety subsystem. Hence, Figs. 8a and 8b can be combined by the node "on?" which represents the state of safety subsystem, seen in Fig. 8c.

After mapping the fault tree into BN, the influence of wind speed and the uncertainty of parameter are considered by using CLM. The range of wind speed has diverse influence on life-lengths of subsystems and assemblies. Therefore, node "$v>v_0$" is added to divide wind speed interval, and it is connected to all subsystems and assemblies. As for uncertainty of parameters, only one parameter in each prior probability distribution is adjusted in this study, which can be described by nodes L_i, where i =1 to 10. The qualitative reliability model of wind turbine based on BN is established, as shown in Fig. 9.

5.2.2. Definition of TTF distributions

Based on the failure data recorded in Windstas for the wind farms in Denmark and Germany during 1994 to 2004, some statistic analyses for the life data of wind turbines have been done in Refs. [11, 24, 25]. The TTF distributions of corresponding subsystems and assemblies are extracted, as presented in Tables 2 and 3, respectively. When the wind speed is larger than cut-out speed (in this case it is 20 m/s), the prior probability distributions of subsystems and assemblies are different. Ref. [26] analyzed which subsystem or assembly's reliability is greatly affected by wind speed. The result showed that the generator is the greatest effect, with yaw assembly and pitch assembly closely behind, whereas mechanical brake, hydraulic assembly, air brake, gearbox, blades are affected not so remarkable. According to

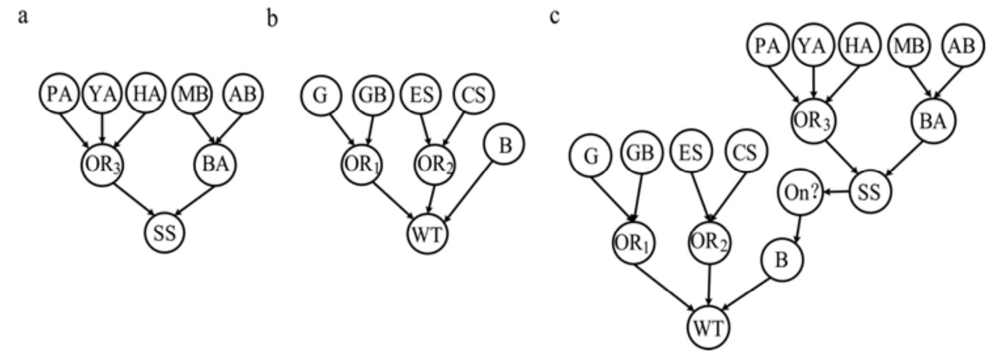

Fig. 8. Mapping fault tree of wind turbine into BN: a) BN model for wind turbine without consideration of safety subsystem; b) BN model for safety subsystem; c) BN model for entire wind turbine system

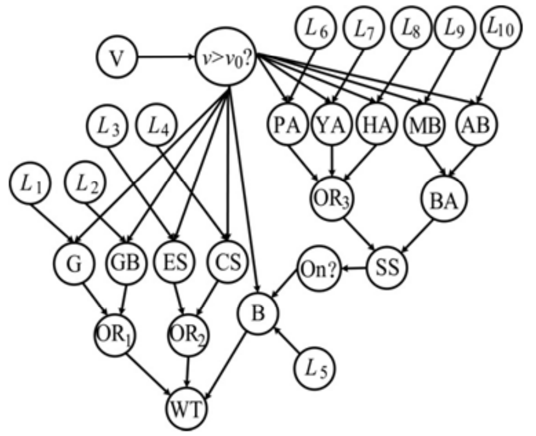

Fig. 9. Qualitative reliability model for wind turbine

Table 2. TTF distributions of subsystems and assemblies

Nodes	TTF distribution when 0<*v*≤20(*h*)	TTF distribution when *v*>20(*h*)
Gearbox	Weibull(12300,1.05)	Weibull(12300,1.05)
Generator	Weibull(76000, 1.2)	Weibull(7600, 1.2)
Electrical subsystem	Weibull(35000, 1.5)	Weibull(35000, 1.5)
Converter subsystem	Exp(1/45000)	Exp(1/45000)
Yaw assemble	Exp(1/65000)	Exp(1/8125)
Pitch assemble	N(84534,506)	N(14089,506)
Hydraulic assemble	Weibull(66000, 1.3)	Weibull(33000, 1.3)
Air brake	Exp(1/100000)	Exp(9/500000)
Mechanical brake	Exp(1/120000)	Exp(1/30000)

Table 3. TTF distributions of blades

	TTF distribution (*h*)	State of safety subsystem (Safe or Failure)	Wind speed (*m/s*)
Blade	N(42000, 663)	Safe	0<*v*≤20
	N(42000, 663)	Safe	>20
	N(42000, 663)	Failure	0<*v*≤20
	N(28000, 663)	Failure	>20

that conclusion, the prior probability distributions judged by experts are shown in column 3 of Table 2.

From Tables 2 and 3, it can be found that the TTF distributions of the subsystems or assemblies obey Weibull(α, β), Exp($1/\lambda$) and N(μ, σ^2), respectively. To simplify the calculation, we consider uncertainty for only one parameter in each distribution, i.e., α in Weibull distribution, λ in exponential distribution and μ in normal distribution.

5.2.3. Reliability assessment of wind turbine

The reliability model is built with Agenarisk© software, and after running for 25 iterations the TTF distributions of wind turbine and its subsystems are obtained. If the wind speed and the uncertainty of parameters are not considered, the reliability of wind turbine at 1000h turns out to be 96.21%, which is quite closed to the result 96.17% in Ref. [11]. Thus, the modeling method and calculating algorithm proposed in this study is with high accuracy.

Now we consider the influence of wind speed and parameters' uncertainty. Assuming that the wind speed obeys Weibull (14, 1.94) and all the regulation factors are set to 0.1. The TTF distributions of subsystems and wind turbine are shown as Fig. 10. In order to make the figure concise, some nodes are hidden. Fig. 11 presents a clear image of TTF distribution of the wind turbine. From Figs. 10 and 11, we can learn that the reliability of the wind turbine at 1000h is 95.18%, and the mean time to failure (MTTF) is 13944h. Obviously, the wind speed and parameters' uncertainty have greatly decreased the reliability.

Meanwhile, from Fig. 11 we can find that firstly the TTF distribution increases within a relatively short period from 0h to around 3000h, and then it keeps declining, which is consistent with the fact that maintenance is not taken into account in this study. It implies that if maintenance is ignored, the TTF is not long enough to meet high availability requirement for wind turbines. Given the target reliability, the corresponding time can be obtained according to TTF distribution. That provides a theoretical foundation for the decision-making of preventive maintenance. In the engineering practice, the life expectancy of wind turbine is about 20 years, and the required technical availability of wind turbines is quite high [29]. Therefore, good reliability design and maintenance management are of crucial importance to the normal operation and economic benefit of wind turbines.

Based on the TTF distribution of wind turbine, the reliability at different points in time can be calculated, and the reliability-to-time curve is drawn, as shown in Fig. 12. In the same manner, reliability-to-time curve without considering the influence of wind speed is also illustrated. Both the curves have the same changing trends, which decrease over time. Compared with the curve not considering the influence of wind speed, the curve considering the influence of wind speed is less reliable, and the gap between them increases with time. For example, at 0h the reliability is 100% for both curves, the gap increases to 5.85% at 10000h. Therefore, the influence of wind speed on wind turbine reliability should not be ignored.

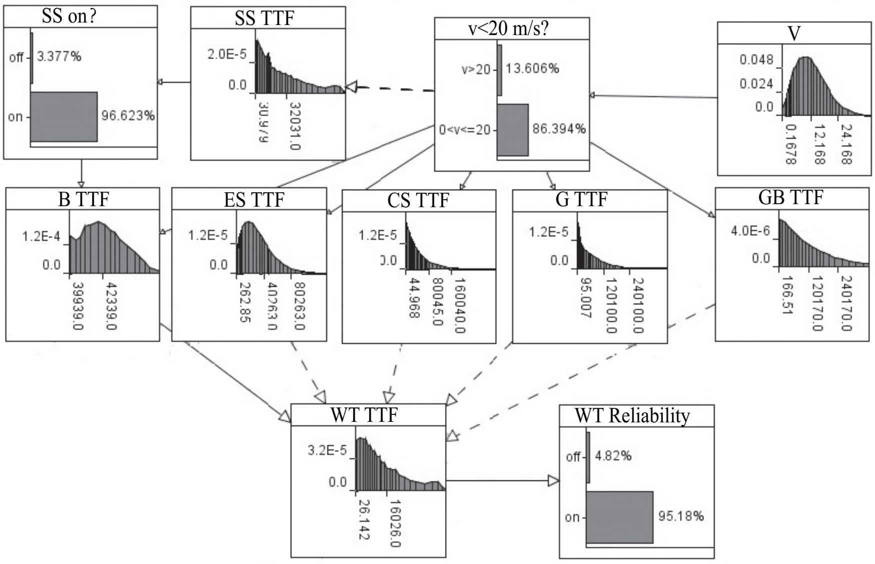

Fig. 10. TTF distributions of wind turbine and its subsystems

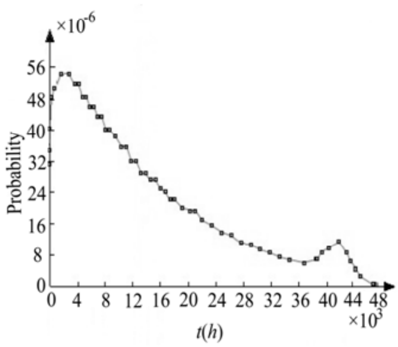

Fig. 11. TTF distribution of wind turbine

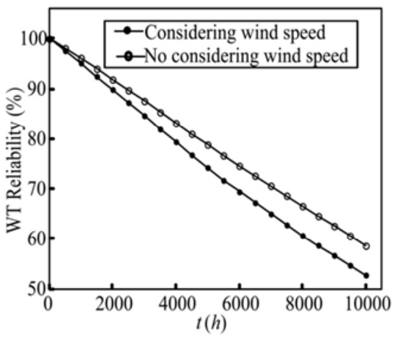

Fig. 12. Reliability-to-time curves of wind turbine

5.3. Reliability over wind speed

In this section, the influence that wind speed acts on the reliability of wind turbine will be further analyzed. Generally, the wind speed is supposed to obey Weibull distribution [19]. The average wind speed $\bar{v}$ can be expressed by the shape parameter α and scale parameter β. Keeping β fixed and by changing α, the relevance between average wind speed and wind turbine's reliability can be analyzed. Running the models under different wind speeds for 25 iterations respectively, the reliabilities at 1000h are evaluated, as shown in Fig. 13. In addition, the corresponding reliabilities under the assumption that the safety subsystem is failed are also calculated, shown also in Fig. 13. Obviously, they have similar variation trends. But if the safety subsystem fails the reliability of wind turbine will be lower, which demonstrates the importance of safety subsystem in protecting the blades and the entire device. Fig. 13 can also show that the gap between the two estimates increases with the values of wind speed. Both Fig. 12 and Fig. 13 illustrate the influence of wind speed on wind turbine's reliability. It's also worth pointing out that this model can be used for wind turbines in different areas with varied wind conditions as long as the prior probability distribution of wind speed is obtained.

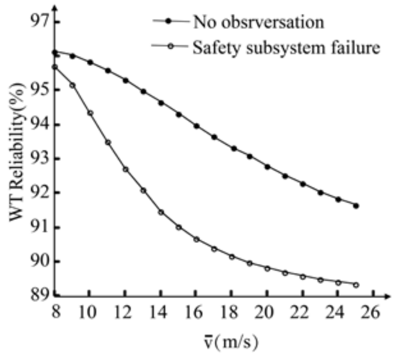

Fig. 13. Reliability of wind turbine varied with wind speed

6. Conclusion and further study

In this article, a reliability model of wind turbine is built based on BN, in which the influence of wind speed is also taken into consideration. The CLM is proposed to direct qualitative modeling. The fault trees are mapped into BN, then the wind speed and parameters' uncertainty are considered. A novel adjustment method based on expectation is presented to modify the prior probability distributions. An approximate inference algorithm involving dynamic discretization is adopted to calculate the TTF distribution of wind turbine. Therefore the reliability of wind turbine can be evaluated. The case study shows that the approach proposed in this article is suitable for reliability assessment of wind turbines. Additionally, the TTF distribution can provide a reasonable guide for the maintenance decision of wind farms.

In this study, we focus only on reliability assessment of wind turbine based on BN. While in practice, maintenance and availability are also very important topics. Hence, we intend to carry out further studies on maintenance decision-making and availability assessment for wind turbines or wind farms based on the theory of Bayesian network in the near future.

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