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Asset management modelling approach integrating structural health monitoring data for composite components of wind turbine blades

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Optimal asset management strategies for wind turbine blades help to reduce their operation and maintenance costs, and ensure their reliability and safety. Structural health monitoring (SHM) can determine the health state of wind turbine blades through implementing damage identification strategies. The main load-bearing structure spar of the wind turbine blade is inside the structure, and hence difficult to inspect. Advanced SHM techniques, such as guided wave monitoring, can be used to monitor the development of cracks in real-time and provide an early indication of their existence. This paper presents a risk-based maintenance model based on the state information provided by SHM. The model is based on Petri nets, and describes the blade degradation and guided wave monitoring processes, inspection and maintenance works. Fatigue test data of composite components is processed to provide input for the model. The reliability of guided wave monitoring is also assessed. The proposed model is able to predict the condition state and expected number of repairs of composite components for wind turbine blades, which can potentially help in making informed asset management decisions during wind turbine blade operation.

Keywords: Asset management, Wind turbine blades, Petri nets, Structural health monitoring, Ultrasonic guided wave monitoring, Reliability of ultrasonic guided wave monitoring.

1. Introduction

To solve the environmental problems and energy shortages we face today, more use of clean energy is required. Wind power is one of the potential ways to generate clean energy. The European Wind Energy Association expects 320 GW of wind energy capacity to be installed in the EU in 2030, 254 GW of onshore wind and 66 GW of offshore wind. That would be an increase of two-thirds from the expected capacity installed in 2020 (192 GW) Corbetta et al. (2015). In the context of rapid development of wind energy, developing robust asset management modelling tools to minimise wind turbine operation and maintenance costs, and assure their reliability and sustainability is of paramount importance.

However, the impact of maintenance on the life cycle of wind farms is complex and uncertain. The choice of maintenance strategy affects the overall efficiency, profitability, safety and sustainability of a wind farm Ren et al. (2021). Different techniques have been used to find the optimal solution. Discrete Bayesian networks are used to construct a general computational framework for risk-based planning of inspections, maintenance and structural health monitoring Ren et al. (2021). A time-dependent stochastic process was employed to optimise maintenance of offshore composite wind turbine blades in Zhang et al. (2021); the gamma process was used to calculate the probability of fatigue failure of blades. A partially-observed Markov decision process was introduced to devise optimal maintenance strategies in Byon and Ding (2010), considering the feasibility of maintenance and multi-state wind turbine deterioration.

Petri nets (PN) are graphical and mathematical modelling tools that can be used not only for visual communication but also for building state equations and algebraic equations Murata (1989). They have been used to model and manage risk in a wide range of fields, including healthcare, civil engineering and aviation Naybour et al. (2019); Netjasov and Janic (2008); Vagnoli et al. (2021). Many researchers also use PN for wind turbine maintenance and failure process simulation. Müller Müller and Bertsche (2021) presented a close-to-reality maintenance optimisation model using high level PN; different detailed points were considered, e.g. the joint use of maintenance capacities as well as aspects of spare parts logistics or weather aspects. Santos Santos et al. (2018) presented an age-dependent preventive maintenance model with an imperfect repair strategy. Le Le and Andrews (2016) proposed an asset model for offshore wind turbine reliability accounting for the degradation, inspection and maintenance processes based on the PN method. However, there have been a limited number of models developed to predict the effects of sensor degradation on condition-based monitoring.

Structural health monitoring (SHM) plays an important role in the health management of wind turbines. SHM can provide engineers with information on the damage evolution status of key parts of the wind turbines in real time, which provides an important reference for maintenance decisions. Nielsen Nielsen et al. (2021) presented a case study demonstrating the methods used to estimate the value of the information delivered by an SHM system. The paper demonstrated how the potential benefit of SHM highly depends on the reliability of the utilised SHM system and how the SHM observations are used for decision-making on inspections and maintenance. Hughes Hughes et al. (2021) formulated a risk-based decision-making framework for SHM that incorporates probabilistic risk assessment; a simple case study was used to illustrate the proposed framework. The above studies have proved the significance of SHM for equipment health management, and the importance of considering SHM in maintenance simulation.

This paper describes an asset management model for composite components of wind turbine blades using a PN method based on fatigue test data. First, Weibull distribution parameters describing the degradation process of composite components are obtained using a manual computation fitting method and numerical optimisation. Second, PNs for inspection and condition-based monitoring are constructed; probability group transitions are used to indicate monitoring accuracy. Changes in the SHM system's health conditions were taken into account. Finally, comparative results of the inspection and condition monitoring in terms of maintenance times are provided; the effect of sensor degradation is also presented.

The manuscript is organised as follows. Sec. 2 introduces the basic concepts of the PN method. Different PN models are developed for degradation, inspection, condition-based monitoring processes in Sec. 3. In Sec. 4, results and discussion are provided. Conclusions are presented in Sec. 5.

2. Basic Petri net concepts

PNs are directed bipartite graphical and mathematical modelling tools, consisting of four simple elements: places, transitions, arcs, and tokens. The Petri net is described by circular nodes called places and square nodes called transitions with a number of arcs connecting places and transitions. The state of a Petri net is described by the distribution of black dots called tokens on the places. The movement of tokens between places is based on the firing rule. A transition is enabled if all of its input positions are marked by a required number of tokens. The transition fires after a delay time or immediately. Firing removes a certain amount of tokens from each input place and adds a certain number of tokens to each output place.

To ease understanding, a simple example is given in Fig. 1. The left side is the initial state. In this paper, all places will be coloured and labelled in black and all transitions in red. Place 1 will be referred to as P1, transition 1 as T1 and so on. In this PN, T1 has one input place, P1, and two output places, P2 and P3. Since P1 is initially marked, the transition is enabled and after a delay, it will fire. After firing, one token is removed from the input place and one/two tokens added to the output places. The arc from T1 to P3 has a weight of 2, so the output to P2 is two tokens. The state after firing is shown on the right side.

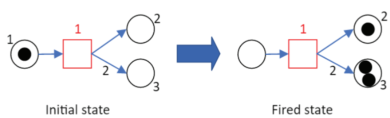

Fig. 1. A simple PN model before and after transition firing

To enhance the functionality of PN, other transitions can be used. A reset transition, when it fires, will reset the marking of specific places to the desired number of tokens Le (2014). A probability group, when it fires, will generate tokens based on an arc's probability weights. A probability group example is shown in Fig. 2. When T1 fires, the probability of the token moving to P1 and P2 is 0.8 and 0.2, respectively. All the places of a probability group will be surrounded by a dashed ellipse. In terms of software implementation, a bespoke research software has been developed in Python.

3. Model description

In this section, the asset management model for composite components of wind turbine blades is presented. It consists of three modules: a failure

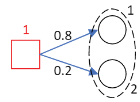

Fig. 2. A simple PN model containing a probability group

model, a monitoring model (including inspection and guided-wave monitoring), and a maintenance model.

3.1. *Failure modelling of composite components*

Modelling the degradation of composite components is a very important input for risk-based maintenance optimisation. This section presents a PN degradation model for composite components based on their damage accumulation data. Places represent different degradation states, and transitions govern the transition times between different states (See Fig. 3). The transition follows a Weibull distribution with scale parameter η and shape parameter β.

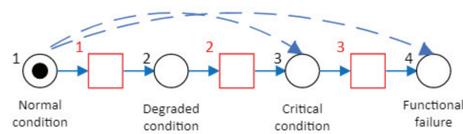

Fig. 3. PN to describe the degradation process of composite components

Delamination due to fatigue loading is one of the most important mechanical failures of laminated composite blades during their design life Zhang et al. (2021); Wessels et al. (2010). Delamination failure accumulation data for cross-ply composites under fatigue conditions are used to fit stochastic distributions, details of the data can be found in Li et al. (2020). Generally, the fatigue process of carbon fibre reinforced resin matrix composites can be divided into three stages: dominated by matrix cracks (stage I), dominated by delamination damage (stage II), and dominated by fibre fracture (stage III) Li et al. (2020). Correspondingly, we can divide the entire life course of composite components into four states, namely normal condition, degraded condition, critical condition and functional failure. Consequently, the time from normal condition to degraded condition is the time elapsed during stage I, and so on. It should be noted that assumptions are made here to reduce the structural investigation to the coupon scale due to the lack of full-scale fatigue data. In Fig. 3, P1-P4 represent the normal, degraded, critical, and failed states respectively.

Approaches for estimating the Weibull parameters can be classified as manual or computational methods. Manual methods perform better for small samples Datsiou and Overend (2018). Fatigue test data for seven groups of CFRP cross-ply laminates are available. It belongs to a small sample, therefore, the manual method is adopted. The median rank estimate calculated by Benard's equation approximation is used, shown in Eq. (1).

$$\hat{F}\left(t_i\right) = \frac{i - 0.3}{n + 0.4} \tag{1}$$

where n is the total number of different degradation states, i is the sequence of certain degradation state.

The Weibull distribution from P1 to P2, from P1 to P3, from P1 to P4 can be fitted directly from the data. In Fig. 3, the blue dotted line indicates that its distribution parameters can be obtained directly by fitting, but cannot be directly applied to PN. The state change indicated by the dotted line also does not exist in the actual PN. However, transition rates between each of the four states are required by the PN model, for example, the transition time from P2 to P3. T1, T2 and T3 are called convolution transitions, as introduced in Andrews (2013). The parameters of a convolution transition can be calculated by numerical integration. An optimisation scheme is adopted to estimate the parameters here Le (2014). The main idea is to take the minimum difference between the total transition time from P1 to P2, P2 to P3 and the transition time directly from P1 to P3 as the objective function to find the optimal solution within a given range of η and β. See Le (2014) for more details. The Weibull distribution parameters for the different convolution transitions are shown in Table 1. We have based the parameter values on Caous et al. (2018), using a relationship between the service life of the wind turbine and the loading period. In the lab conditions, it is unrealistic to perform a loading cycle on the actual size of the turbine, therefore the tests are carried out at a coupon level. Then the fatigue test data described above are normalized to 1.

Table 1. Transition parameters of Weibull distributions for degradation transition.

Type	Parameters
T1	η = 0.4935, β = 2.9000
T2	η = 0.1595, β = 2.1283
T3	η = 0.3838, β = 2.0020

3.2. *Model for condition-based monitoring and inspection process*

Periodic inspections and condition-based monitoring (CBM) are commonly used by wind farm owners and operators. PNs are developed for those two processes in this section.

3.2.1. *Inspection process*

The inspection process is straightforward. Most wind farms perform scheduled inspections on a regular basis. Some defects can be detected by visual inspection, such as corrosion and leakage, or surface cracks in faulty blades. Fig. 4 illustrates the PN modelling inspection process of the composite components. P1 to P4 represent the true degradation states (normal condition, degraded condition, critical condition and functional failure) of composite components. T1 to T3 represent transitions between each state. The transitions follow a Weibull distribution with parameters obtained from fatigue experimental data (see Sec. 3.1). T8 models periodic inspection and fires at regular intervals. After T8 fires, P9, P10, P11 and P12 will each receive one token. If the current state of the composite component is in a degraded condition, then T5 will fire immediately.

One token will be generated in P6 or P14, with the probability relating to P14 representing the probability of an error in the inspection process. The marking of P14 therefore indicates the number of false inspections (as do P13, P15, and P16). The error of inspection is set to 90%. The false inspection is when the inspection fails to determine the level of degradation. If the token is moved to P6, T13 will be fired after a delay. T13, T14, and T15 represent the maintenance action. If any of them are fired, the composite component will return to normal condition, that is, the tokens in P1 to P4 will be reset to the initial state. After the simulation, the markings of P17 to P19 are equal to the number of occurrences of each repair action; the markings of P5 indicate the number of times the inspection detected a normal condition; the markings of P13 to P16 represent the number of inspection failures. More details about maintenance will be introduced in Sec. 3.3. The inhibitor arcs Le (2014) from P1 to T9, P2 to T10, P3 to T11, and P4 to T12 allow T9, T10, T11 and T12 to empty P9, P10, P11 and P12 if the component is not at a corresponding level of degradation. The inhibitor arcs from P6 to T2, P7 to T3 are used to prevent further degradation when maintenance is underway.

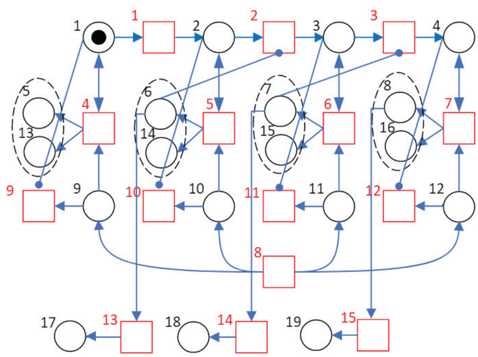

Fig. 4. PN to describe the inspection process of composite components

However, inspections have their limitations. All blade parts are load-bearing, but the spar structure is typically responsible for the largest part of the resistance to aerodynamic loads. The spar structure is located inside the blade and its damage status cannot be obtained by visual inspection. The SHM method described in the next section will functionally supplement inspection.

3.2.2. *Ultrasonic guided wave monitoring and its reliability*

SHM can determine the health state of wind turbine blades by implementing damage identification strategies. Different established SHM techniques are employed for monitoring wind turbine blades, including acoustic emission Liu et al. (2020), vibration analysis Liu (2013), strain monitoring Khadka et al. (2021), and ultrasonic guided wave monitoring Wang et al. (2018); Wu et al. (2022). The use of ultrasonic guided waves to identify damage has become a popular method due to its robustness and fast execution, as well as the advantage of being able to inspect large areas and detect minor structural defects. Fig. 5 shows the PN modelling the CBM process (in this paper, ultrasonic guided wave monitoring) of the composite components. The parameters and functions of P1 to P4 and T1 to T3 are the same as for the inspection PN model. The visual inspection and SHM are most likely to identify different types of degradation since they act on different parts of the blades, and therefore the degradation parameters could be different. In this paper, we assume that the component damage behaviour detected by inspection and CBM is the same. The effect of this assumption will be considered in future research.

Ultrasonic guided wave monitoring technology can monitor the health of composite parts in real time after the monitoring system is installed on a wind turbine blade. It is more efficient than the inspection process. However, due to changes in the operating environment and the effects of ageing, the sensor itself undergoes a degradation process that degrades its performance over time. There is a need to consider the false alarm rate of the monitoring system Liu et al. (2019); Falcetelli et al. (2021). P5 to P7 and T4 to T5 (same as P11 to P13, T9 to T10, P17 to P19, T14 to T15, P23 to P25, and T19 to T20) represent the degradation process of the monitoring system. Three states of the monitoring system are considered, namely normal, degraded, and critical. As the degradation progresses, the monitoring accuracy decreases, that is to say, the false alarm rate increases. Changes in monitoring accuracy will be indicated by probability groups. It is assumed that the degradation of sensors can be characterized by Weibull distributions and that the degradation parameters are known in advance. Weibull parameters can be estimated by maximum likelihood estimation and many other existing methods, as long as historical failure/degradation data are known. In this study, the transition T4 and T5 follow a Weibull distribution with η_{T4}=28.0, β_{T4}=6.5 as well as η_{T5}=28.0, β_{T5}=5.5. The detection accuracy of the monitoring system for normal, degradation, and critical conditions is 95%, 70%, and 10%, respectively. T6 to T8 (same as T11 to T13, T16 to T18 and T21 to T23) represent real time monitoring. They fire periodically at a very short interval. In this study, the interval is set to 0.02. T24 to T32 represent the maintenance action.

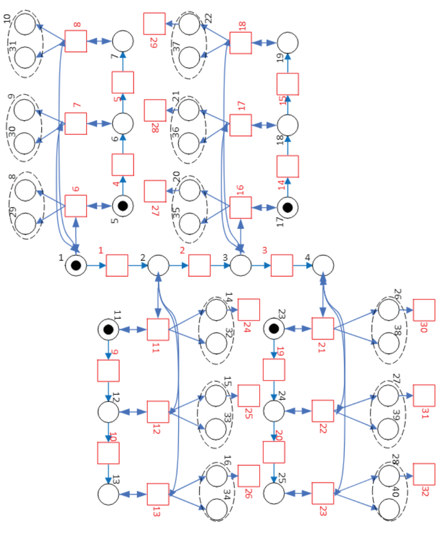

Fig. 5. PN to describe the ultrasonic guided wave monitoring of composite components

3.3. *Maintenance model*

Corrective and preventive maintenance are considered in this work. In the modelling process of this paper, it is assumed that after the composite components are repaired, their functions will be fully restored. Probability groups enable maintenance policies to be based on the condition revealed by inspection or CBM-monitored conditions rather than the true conditions, in line with the actual situation. The inspection process and CBM correspond to corrective and preventive maintenance, respectively. T13 to T15 in Fig. 4 represent corrective maintenance strategies. T24 to T32 represent preventive maintenance strategies. Different failure states correspond to different maintenance actions. In this paper, a degraded condition refers to the observation of damage above wear and tear, requiring minor repairs (Type I). A critical condition is when significant damage is observed, requiring major repairs (Type II). A functional failure means a failure occurs, and then an exchange is required (Type III).

4. Results and discussion

Based on the above model parameters, the number of simulations was set to 1,000,000, and some level of convergence has been reached in terms of the number of different repair actions reaching a constant or stable value. We performed the Petri nets modelling on a multicore server with Intel Xeon E5-1620 v4 Processor (3.50 GHz) and 32 GB of installed RAM. A single simulation took about 0.0076 seconds. This section first presents a comparison of the number of repairs per unit time based on the inspection process and CBM, shown in Fig. 6. Inspection interval is set to 0.15. But, the inspection interval used here is not the optimal value, and future research will use numerical optimization methods to get the optimal value. Compared with the system monitored by inspection, the system monitored by CBM has a higher number of repairs for type I, but a lower number for type II and type III. CBM is monitored more frequently than inspection, and can notify engineers more quickly to complete repairs before failure conditions deteriorate further. The maintenance cost of Type I will be significantly less than that of Type II and Type III.

The perfect CBM system and degraded CBM system are compared in Fig. 7. It is observed that a perfect CBM system can completely prevent

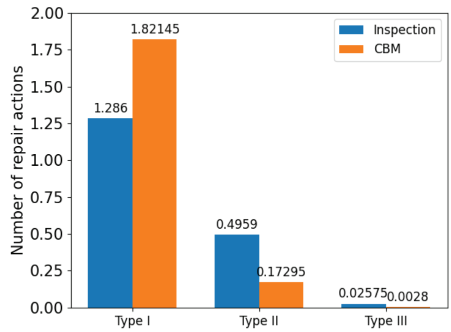

Fig. 6. Inspection and CBM comparison of the number of different maintenance types per unit time

the system from deteriorating to the worst case and greatly reduce the repair times of Type II. However, a perfect monitoring system is not practical. The results show the need to consider sensor degradation in the maintenance simulation.

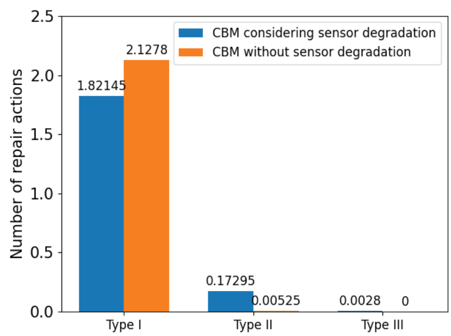

Fig. 7. CBM with/without sensor degradation comparison of the number of different maintenance types per unit time

5. Conclusions

An asset management PN model for composite components of wind turbine blades integrating SHM data is presented in this paper. This incorporates a stochastic degradation model of composite components based on experimental data. An inspection process and CBM are both considered in the PN models. It has been demonstrated that compared with the inspection process, the CBM system can more efficiently monitor changes in system status, notifying of the need for engineering maintenance in a timely manner. It can therefore effectively curb significant deterioration of the system and reduce the need for high-cost maintenance. Consideration of imperfect SHM systems has proven to be critical. The monitoring accuracy varies with the state of the SHM, and the monitoring accuracy has a great influence on the numerical results. Future research will extend this work by including detailed maintenance strategies and the reliability of the SHM system.

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