Reliability Analysis of Floating Offshore Wind Turbines Support Structure using Hierarchical Bayesian Network

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Comprehensive reliability analysis of the support structure of a floating offshore wind turbine is implemented by utilizing a hierarchical Bayesian network model that consists of failure propagation and failure behavior layers. In the failure propagation layer, failure probability, reliability, failure rate, mean time to failure with respect to service time are estimated. Moreover, the primary failure contributors to the support structure are determined. In the failure behavior layer, correlations among failure modes are investigated, based on which, impacts of each failure mode on others are clarified. The results of this study are verified by comparing with what was concluded by the fault tree analysis. Recommendations such as the maintenance interval of the support structure should be less than 101 days within the service time of nine years and operational skill training for operators are concluded.

Keywords: Reliability analysis, hierarchical Bayesian network, support structure, floating offshore wind turbine, correlation analysis, failure behavior.

1. Introduction

As a promising type of renewable energy, wind energy has been installed tremendously worldwide during the last decade (Burke and Stephens 2018). Moreover, mandatory plans of increasing wind energy capability confirming the significant growth in the future, e.g. European Union (EU) plans to raise the wind energy proportion up to 31.6%-48.7% in 2050, motivated by which more than 3 GW offshore wind energy capacity has been installed within 2017 around EU (Liobikienė and Butkus 2017).

Offshore wind energy benefits from flexible installation, environment-friendly, higher and constant wind speed, space-saving, and more workdays being regarded as the succedaneum of onshore wind energy (Bagbanci et al. 2012). A practical case is that Chinese government is planning to develop approximately 4 GW offshore wind energy capacity before 2020 (Lin et al. 2016).

However, the advantage of applying offshore wind energy relies mainly on the high reliability and availability of offshore wind turbines (OWTs), for weather windows of maintenance can be difficult to obtain especially in winter. Unfortunately, OWTs tend to fail more in frequency than onshore facilities as consequences of harsh and extreme sea conditions, system complexity, and more complex functions (Santos et al 2015a). Frequent failures and maintenance processes lead to low availability of OWTs and give rise to vast economy loss of wind farms (Santos et al 2015b; Kang et al. 2019).

On this basis, efforts been made to carry out reliability analysis of OWTs at both global and system levels in order to secure their high reliability and availability. Marquez et al. (2016) identified crucial components and factors that result in malfunctions of a wind turbine by fault tree (FT) and binary decision diagram (BDD) joint method, and concluded that the yaw motor is the most failure-prone component and that abnormal vibration is the commonest contributor to wind turbine malfunctions. Arabian-Hoseynabadi et al. (2010) employed failure mode and effects analysis (FMEA) method to ascertain the most critical failure mode of a typical 2MW indirect drive variable speed wind turbine, which is materials failure among others. Bharatbhai (2015) applied failure mode effects and criticality analysis (FMECA) identified key components susceptible to failure are turbine blades and lubrication system. Kang et al. (2019) analyzed the reliability of a floating offshore wind turbine (FOWT) by fault tree analysis (FTA) method and pointed out that failure rate of the FOWT is 7.3 failures per year, which is approximately 13% larger than what was derived from data collected. Zhang et al. (2016) conducted a reliability analysis of a FOWT using dynamic FTA, indicated that the maintenance interval of the FOWT should be less than 24 days.

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Concerning the reliability analysis for wind turbines systems, Liniger et al. (2018) assessed the failure rate of the pitch system of a wind turbine by simulation methods. Li et al. (2019) evaluated the reliability of gearbox of a wind turbine by degradation-Hidden-Markov model and concluded that the reliability of wind turbine bearings decreases sharply after the service period of 108 months. Tazi et al. (2017) developed a hybrid cost-FMEA to analyze the reliability of FOWTs gearbox and blades system. Fischer et al. (2015) analyzed the failure behavior of converters and revealed that insufficient protection of converters has a strong impact on malfunctions of the generator. Kang et al. (2016) analyzed the reliability of the support structure of a FOWT by FTA method and the results indicate that extreme weather conditions are the main contributors to malfunctions of the support structure.

Currently, however, reliability analysis of FOWTs and their systems are concentrated on failure propagation with two tasks: failure rate prediction and crucial components identification. Specifically, FTA is good at tracing paths of failures propagation within the system (e.g. component failures affect sub-systems and then result in system malfunctions) while failure behaviors are neglected e.g. failure modes and correlations among them. The opposite is true for the FMEA and the upgraded FMECA (only implemented in failure behavior aspect and the failure propagation is neglected). To this end, this paper developed a hierarchical Bayesian network (HBN) model comprising both failure propagation and failure behavior layers to analyze the reliability of the support structure of the FOWT used in Kang et al. (2019). On this basis, reliability indexes, weak links of the FOWT are ascertained in the failure propagation layer. Correlations among failure modes are analyzed in the failure behavior layer. The software GeNIe in version 2.1 is employed to construct the HBN model in this study.

The rest of this paper is organized as follows. Section 2 introduces the methodology of constructing the HBN model. Results are shown in section 3. Conclusions in Section 4.

2. The Methodology of the HBN Model

Bayesian networks (BNs) are powerful tools for reliability modeling, analysis, and estimation. The capability of dependency analysis identifies BNs as useful tools in reliability engineering. BNs are comprised of nodes and edges that represent variables and their causal relations, respectively (Langseth and Portinale 2007). The detailed methodology of BNs can be reached in Bobbio et al. (2001). HBNs are special BNs developed for representing hierarchical systems, which typically have three forms: nested representation, tree representation, and standard representation (Gyftodimos and Flach 2002). The dependences between nodes in a HBN can be represented by a corresponding standard BN (known as standard representation form) after applying the flatten algorithm. The inference of a HBN follows the same way as a standard BN in the standard representation form of a HBN. An example of HBN is illustrated in Fig. 1.

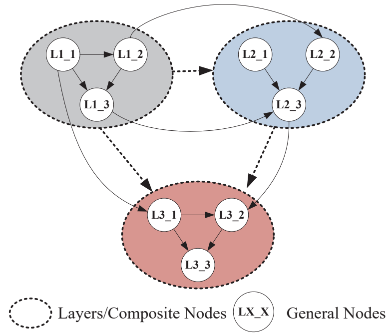

Fig. 1. An example of HBN

The HBN model of the support structure in this study consists of two layers: the failure propagation layer and the failure behavior layer. The sub-BN model in the failure propagation layer analyzes the failure mechanism of the support structure like the way how a failure of a component leads to certain sub-systems fails and then results in the support structure malfunctions. The failure data and the fault tree logic established by Kang et al. (2019) are employed in the failure propagation layer of the constructed HBN model. The main tasks of the failure propagation layer are to predict reliability characteristics of the support structure and identify critical factors lead to support structure malfunctions.

Furthermore, the failure behavior layer is created to model the behavior of the support structure malfunctions. 31 basic factors that give rise to malfunctions of the support structure are classified into four categories namely structural defect or bad design (SDBD), extreme environment (EE), abnormal operations (AO), and materials damage and degeneration (MDD). Eight failure modes were considered in this study namely lines broken (LB), tower failure (TF), tower collapse (TC), foundation failure (FF), system unbalance (SU), system movement (SM), abnormal vibration (AV), and abnormal functions (AF).

The support structure is fundamental but the largest assembly of the FOWT typically consists of a tower, a floating foundation, and a mooring system (Uzunoglu et al. 2016). The tower resists force (and movement) of the FOWT, while the mooring system and the floating foundation provide stable buoyancy and the exact fixation to the FOWT. The HBN model in the standard representation form of the support structure is illustrated in Fig. 2. For model clarity reason, the basic nodes in the failure propagation layer are represented by alternative symbols in the failure behavior layer e.g. B02 and B02 are the same node in the real HBN model. The conditional probability tables of nodes in the failure behavior layer are listed in Appendix A and nodes definition of the HBN model is shown in Appendix B.

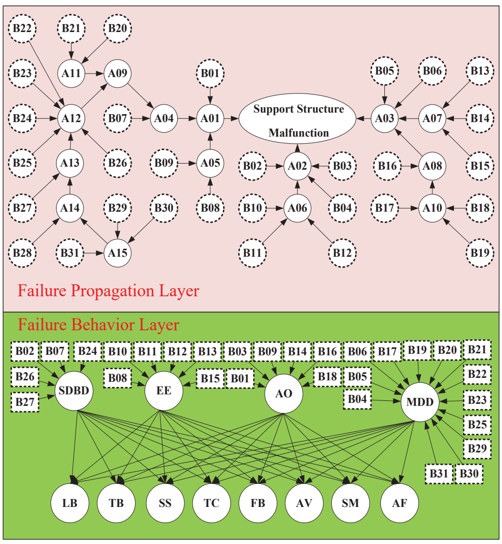

Fig. 2. The HBN model in standard representation form of the support structure (details are listed in Appendix A and B)

3. Results

3.1. In the failure propagation layer

The predicted reliability of the support structure is approximately 0.03 after one year service with the mean time to failure (MTTF) 2601*h*. As a comparison, the MTTF was concluded to be 2680*h* by FTA and which is reported larger than that from data collection (Kang et al. 2019). The forecasted reliability, failure probability, failure rate, and MTTF of the support structure are plotted in Figs. 3 and 4, respectively. The forecasted MTTF indicates that the maintenance interval of the support structure should be less than 101 days during nine years' service.

The failure rate curve with respect to time was fitted by Gaussian function (with the lowest root mean squared error, 0.002), see Eq. (1). Floating foundation is more reliable than mooring system and tower. For instance, on the initial day of working, the reliability of floating foundation, mooring system, and tower are 0.99988, 0.99973, and 0.99965, respectively.

$$FR = 3.6e^{-(\frac{11.41-t}{46.27})^2} - 0.05e^{-(\frac{0.92-t}{1.23})^2} \qquad (1)$$

In which, FR and t are failure rate and service time of the support structure.

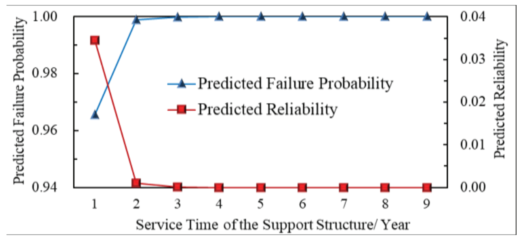

Fig. 3. The predicted reliability and failure probability of the support structure

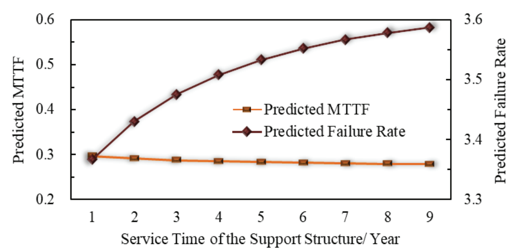

Fig. 4. The forecasted failure rate and MTTF of the support structure

The tower contributes with 36% of failures of the support structure, followed by mooring system (34%) and floating foundation (30%). Tower malfunctions are mostly caused by tower collapse (the possibility of which is 83%). Mooring lines broken, results from abnormal stress, give rise to more than 60% mooring systems failures. Dropped object hits floating foundation acts as the most crucial event of floating foundation malfunctions which contributes about 89% failures to the floating foundation. The primary contributors to support structure malfunctions are displayed in Fig. 5.

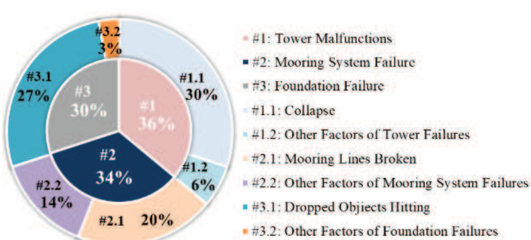

Fig. 5. The primary contributors to support structure malfunctions

With the analysis results aforementioned, a precise and timely weather forecast is recommended for preventing the support structure malfunctions caused by harsh environmental conditions e.g. strong waves and storms. Preventive actions e.g. clear excessive objects on the floating foundation and checking loose structures of the support structure may be executed in advance according to the outcomes of the weather forecast. Meanwhile, abnormal working conditions like abnormal stress call for reinforcement of the strength and preserve larger design margin of mooring lines in the design stage.

3.2. In the failure behavior layer

In the failure behavior point of view, predicted probability of system unbalance is some 0.33 at the end of the first year, followed by abnormal functions (0.3), system movement (0.25), tower collapse (0.24), foundation failure (0.23), abnormal vibration (0.23), lines broken (0.21), and tower failure (0.17).

Abnormal operation is a chief factor leads to stoppages of the support structure, the probability of which is 0.56 under the condition of system failure, followed by structural defect or bad design (0.49), materials damage and degeneration (0.31), and extreme environment (0.06).

Hence, having sensors to monitor vibration signals of crucial parts of the support structure is highly recommended. Besides, other measures as reinforcing the strength of mooring lines and clean superfluous objects on the floating foundation are also suggested (agree with that what have been concluded in the failure propagation layer). Redesign weak parts of the support structure is also an unneglectable means to secure the support structure functioning. Besides, operational skill training and ordering standard operation procedures are required according to the results of the analysis.

BNs hold advantages in modeling and analyzing the dependence of systems by their capability of prediction and diagnosis support information propagation capabilities, also known as information updating. Based on the HBN model, correlations among failure modes are investigated and the results are listed in Fig. 6, in which the value in each cell represents the posterior probability of a failure mode with respect to another e.g. 0.52 in Fig. 6 denotes the probability of system unbalance (SU) is 0.52 under the condition that the failure mode system movement (SM) is observed, mathematically represented by $P\{SU=true \mid SM=true\}=0.52$.

	LB	TB	SM	FB	AV	TC	SU	AF	Average	Rank
LB	1	0.28	0.41	0.36	0.44	0.38	0.49	0.42	0.473	1
TB	0.38	1	0.38	0.34	0.41	0.37	0.48	0.42	0.473	1
SM	0.34	0.26	1	0.38	0.46	0.37	0.52	0.41	0.468	3
FB	0.34	0.26	0.42	1	0.44	0.36	0.49	0.42	0.466	4
AV	0.35	0.26	0.43	0.38	1	0.37	0.5	0.42	0.464	5
TC	0.33	0.26	0.39	0.34	0.4	1	0.47	0.4	0.449	6
SU	0.31	0.25	0.4	0.34	0.4	0.35	1	0.4	0.431	7
AF	0.29	0.24	0.34	0.32	0.38	0.32	0.44	1	0.416	8
OV	0.21	0.17	0.33	0.24	0.23	0.27	0.25	0.3	—	—

OV: Predicted probabilities of failure modes

Fig. 6. The results of correlation analysis among failure modes of the support structure

According to the results of the aforementioned correlation analysis, the following conclusions are reached:

(1) All failure modes of the support structure have a positive (on the numerical standpoint) impact on others since failure probability of a failure mode will increase more or less when other failure modes happens e.g. the predicted probability of mooring lines broken is 0.21, which, however, increased to 0.35 given that abnormal vibration was observed.

(2) Mooring lines broken and tower failure are top failure modes that affect other failure modes followed by system movement, foundation failure, abnormal vibration, tower collapse, system unbalance, and abnormal functions. However, impacts vary slightly (between 0.166

and 0.223). Hence, in engineering cases all failure modes are recommended to be considered.

(3) System unbalance is the frailest failure mode of the support structure, which is influenced strongly by others. On the contrary, tower failure is the most robust failure mode. Among all failure modes, System unbalance is prominently impacted by system movement and abnormal vibration.

4. Conclusions

A hierarchical BN model consisting of failure propagation and failure behavior layers was developed for analyzing the reliability of the support structure of a floating offshore wind turbine.

The predicted reliability and corresponding MTTF suggest that the maintenance interval of the support structure should be less than 101 days within the service time of nine years. The primary failure contributors to the support structure malfunctions such as tower collapse caused by strong waves and storms were determined according to the results of the HBN model. Additionally, in the failure behavior layer, system unbalance is recognized as the commonest failure mode of the support structure followed by abnormal functions, system movement, tower collapse, foundation failure, lines broken, and tower failure. On these bases, measures of ensuring safe operation and high reliability of the support structure were recommended.

Correlations among failure modes were investigated in the failure behavior layer of the HBN model. Impacts of each failure mode on others were determined for demonstrating a deep-going understanding of failure behaviors of the support structure.

However, the correlation analysis in this study focuses mainly on failure modes at an elementary level, model deeply correlations among failure modes as well as among components are expected to be implemented in the future study.

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Appendix A. The Conditional Probability Tables of Nodes in the Failure Behavior Layer

SDBD		T								F							
EE		T				F				T				F			
AO		T		F		T		F		T		F		T		F	
MDD		T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F
LB	T	0.9	0.7	0.8	0.6	0.4	0.2	0.3	0.1	0.8	0.6	0.7	0.5	0.3	0.1	0.2	0
	F	0.1	0.3	0.2	0.4	0.6	0.8	0.7	0.9	0.2	0.6	0.3	0.5	0.7	0.9	0.8	1
TF	T	0.7	0.6	0.6	0.5	0.3	0.2	0.2	0.1	0.6	0.5	0.5	0.4	0.2	0.1	0.1	0
	F	0.3	0.4	0.4	0.5	0.7	0.8	0.8	0.9	0.4	0.5	0.5	0.6	0.8	0.9	0.9	1
TC	T	0.9	0.7	0.8	0.6	0.4	0.3	0.4	0.2	0.7	0.5	0.6	0.4	0.3	0.1	0.2	0
	F	0.1	0.3	0.2	0.4	0.6	0.7	0.6	0.8	0.3	0.5	0.4	0.6	0.7	0.9	0.2	1
FF	T	0.8	0.5	0.7	0.4	0.5	0.2	0.4	0.1	0.7	0.4	0.6	0.3	0.4	0.1	0.3	0
	F	0.2	0.5	0.3	0.6	0.5	0.8	0.6	0.9	0.3	0.6	0.4	0.7	0.6	0.9	0.7	1
AV	T	1	0.6	0.9	0.5	0.6	0.2	0.5	0.1	0.9	0.5	0.8	0.4	0.5	0.1	0.4	0
	F	0	0.4	0.1	0.5	0.4	0.8	0.5	0.9	0.1	0.5	0.2	0.6	0.5	0.9	0.6	1
AF	T	0.8	0.6	0.5	0.3	0.6	0.4	0.3	0.1	0.7	0.5	0.4	0.2	0.5	0.3	0.2	0
	F	0.2	0.4	0.5	0.7	0.4	0.6	0.7	0.9	0.3	0.5	0.6	0.8	0..5	0.7	0.8	1
SU	T	1	0.7	0.9	0.6	0.7	0.4	0.6	0.3	0.7	0.4	0.6	0.3	0.4	0.1	0.3	0
	F	0	0.3	0.1	0.4	0.3	0.6	0.4	0.7	0.3	0.6	0.4	0.7	0.6	0.9	0.7	1
SM	T	0.9	0.5	0.9	0.5	0.6	0.2	0.6	0.2	0.7	0.3	0.7	0.3	0.4	0	0.4	0
	F	0.1	0.5	0.1	0.5	0.4	0.8	0.4	0.8	0.3	0.7	0.3	0.7	0.6	1	0.6	1

(i) LB: Lines Broken; TB: Tower failure; TC: Tower Collapse; FB: Foundation failure; SU: System Unbalance; SM: System Movement; AV: Abnormal Vibration; AF: Abnormal Functions.

(ii) SDBD: Structural Defect or Bad Design; EE: Extreme Environment; AO: Abnormal Operations; MDD: Materials Damage and Degeneration.

(iii) T: True; F: False.

Appendix B. Nodes Definition of the Hierarchical BN

Code	Events	Layer	Code	Events	Failure Rates (h^{-1})
A01	Mooring system failure		B01	Human error	6.00E-6
A02	Tower malfunctions		B02	Resonance	5.00E-6
A03	Floating foundation failure		B03	Faulty welding of tower	7.00E-6
A04	Devices failure		B04	Material fatigue	1.10E-5
A05	Extreme sea condition		B05	Pillar damage	5.00E-6
A06	Collapse due to environment		B06	Capsize	1.00E-6
A07	Hit by dropped objects		B07	Anchor failure	1.80E-5
A08	Watertight fault	FPL	B08	Poor operation environment	7.80E-5
A09	Other devise failure		B09	Insufficient emergency measurement	1.00E-6
A10	Pipe joint failure		B10	Strong wind/wave	5.00E-5
A11	Fairlead failure		B11	Lightning Strike	7.00E-6
A12	Mooring lines broken		B12	Storm	5.50E-5
A13	Mooring line breakage		B13	Typhoon	1.00E-4
A14	Mooring lines wear		B14	Planes crash	1.00E-6
A15	Abnormal mooring line		B15	Biological collision	5.00E-6
SDBD	Structural Defect or Bad Design		B16	Inefficient detection	8.65E-6
EE	Extreme Environment		B17	Pipe joint corrosion	1.30E-5
AO	Abnormal Operations		B18	Pipe joint weld defect	3.00E-6
MDD	Materials Damage and Degeneration		B19	Pipe joint fatigue	3.00E-6
LB	Lines Broken		B20	Fairlead corrosion	1.00E-5
TF	Tower Failure	FBL	B21	Fairlead fatigue	1.70E-5
SU	System Unbalance		B22	Transitional chain wear	1.01E-5
TC	Tower Collapse		B23	Friction chain wear	6.93E-6
FF	Foundation Failure		B24	Mooring winch failure	8.00E-6
AV	Abnormal Vibration		B25	Buoys friction chain wear	4.19E-6
SM	System Movement		B26	Anchor pickup device damage	5.56E-6
AF	Abnormal Functions		B27	Abnormal stress	4.07E-5
			B28	Invalid maintenance	3.78E-5
	FPL: Fault Propagation Layer; FBL: Failure Behavior Layer.		B29	Mooring lines wear	1.60E-5
			B30	Mooring lines fatigue	1.70E-5
			B31	Mooring lines corrosion	5.38E-6

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