Combining Drone-based Monitoring and Machine Learning for Online Reliability Evaluation of Wind Turbines

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***Abstract*—The offshore wind energy is increasingly becoming an attractive source of energy due to having lower environmental impact. Effective operation and maintenance that ensures the maximum availability of the energy generation process using offshore facilities and minimal production cost are two key factors to improve the competitiveness of this energy source over other traditional sources of energy. Condition monitoring systems are widely used for health management of offshore wind farms to have improved operation and maintenance. Reliability of the wind farms are increasingly being evaluated to aid in the maintenance process and thereby to improve the availability of the farms. However, much of the reliability analysis is performed offline based on statistical data. In this article, we propose a drone-assisted monitoring based method for online reliability evaluation of wind turbines. A blade system of a wind turbine is used as an illustrative example to demonstrate the proposed approach.**

***Index Terms*—Bayesian network, Machine Learning, Offshore Wind Industry, Reliability, UAV**

I. Introduction

To have a sustainable and clean planet, renewable energies play a vital role. Among the renewable energy sources, offshore wind energy is a promising one. It is estimated that by 2030, up to 7.7% of Europe's overall electricity demand will be fulfilled by offshore wind energy through the installation of wind farms with 66 Gigawatt production capacity [1]. The only way to achieve this and to make this type of energy widespread, it should be cost-competitive with traditional energy sources. Thus, the Levelized Cost of Energy (LCoE) generated by offshore wind farms, valued at 80–100 €/MWh [2], should be reduced down to an acceptable level. The long-term forecast of UK government has envisaged that by 2050, the LCoE of offshore wind energy to be reduced to the level close to that of the LCoE of onshore wind energy, i.e., approximately 60 €/MWh [3].

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Turbines efficiency and production rely on operation and maintenance procedure that consumes the LCoE up to 35 percent [4]. The overall inspection and repair time for an offshore wind farm can randomly prolong due to inaccessibility issues caused by safety restrictions, inappropriate weather, etc. Due to inaccessibility problems, an onshore wind turbine with 97 percent availability can have 76 percent availability when it is located in about 15 km offshore [5]. Therefore, reliability and availability are critical factors for cost-efficient production of energy using offshore wind systems.

As the reliability of wind turbines plays a crucial role in their performance and maintenance decision, numerous efforts have been made for reliability analysis of wind turbines. Different reliability analysis models such as fault trees [6], Markov chains [7], Bayesian networks (BN) [8], etc. have been utilised to model the failure behaviour of wind turbines. Subsequently, statistical failure data of wind turbines' components are used in these models to evaluate the wind turbine reliability. In most of the cases, as the practical operational scenarios or profiles of the components are not taken into account, such reliability evaluation fails to consider the practical scenario properly. Therefore, changes in reliability under different operational conditions should be determined for effective preventive maintenance and to improve system operation. As the factors affecting reliability changes continuously over time, real-time/online reliability evaluation is an ideal solution for capturing effects of such changes in reliability. Some of the above-mentioned techniques have been adapted to perform online reliability analysis where data monitored and recorded by sensors and instruments are utilised to update real-time reliability.

As blades are a major component of wind turbines, up to 25 percent of the production of a turbine depends on its healthy blades [9]. Hence, failure of blades could lead to unscheduled downtime and substantial monetary loss. Variable wind loads and other environmental conditions including dust, lightening, and icy weather make blades a fragile component of wind turbines. For this reason, reliability analysis and health monitoring of blades received significant interest from industry and academia. Rope-based inspection by human and telescope observation are traditionally used for blades' health monitoring and defects detection on the surface of the blades. These approaches are time-consuming, expensive and they have low detection efficiency and high-risk factors. Different sensors such as acoustic emission (AE) sensors, vibration sensors, ultrasonic sensors and strain sensors have been used for the monitoring of blades [10]. Other more advanced sensors such as fibre Bragg grating sensors [11] and scanning laser Doppler vibrometer sensors [12] have also been utilised for wind turbines' blades health monitoring. Although sensor-based defect detection of wind turbine blades is shown to be useful, further visual inspections are still needed to obtain the details of the defects.

In recent decades, the utilisation of unmanned aerial vehicles (UAVs), e.g. drones, for remote monitoring has gained popularity. In addition to monitoring civil structures such as roads and bridges, UAVs are recently being commercially used to inspect the surface conditions of wind turbines' components, especially the blades of wind turbines. Although drones are being used for structural health monitoring of wind turbines, especially for blades, the monitoring knowledge is rarely used for online reliability evaluation of wind turbine systems. In this article, we look at this issue and proposed a drone-based wind turbine monitoring architecture which aims at utilising drone-based monitoring knowledge for online evaluation of reliability.

II. Related Works

A. Drone-based Monitoring in offshore wind industry

In the offshore wind industry, drones have been used in different ways such as for remote inspection, facilitating maintenance activities etc. Thermography and visual inspections are two commonly used ways for UAV-based monitoring. The cost-benefit evaluation of the UAV-based or drone-based blade inspection is an essential step before using the technology in the industry and [13] has analysed the cost-benefit of UAV-based structural inspection of the wind turbines. The paper has addressed different comparisons and quantitative cost analysis between conventional wind turbine structural inspection and the UAV-based one. The report shows a significant reduction in the cost and operational time in using UAV-based inspection.

Regarding the drone-based inspection, in the experimental study shown in [14], multicopters with vision and LiDAR sensors have been used for inspection of turbine's blades to guide the climbing robots while performing maintenance of the blades of wind turbines. A data-driven framework was proposed by Wang and Zhang [15] for automatic crack detection on the surface of wind turbine blades. For the detection and classification of the cracks, they utilised a set of models such as the LogitBoost, Decision Tree, and Support Vector Machine. Peng and Liu [16] utilises the images taken by UAVs to propose an analytical crack detection method for wind turbine blades. At first, they performed some pre-processing of the images taken by drones to improve their quality. Once the noises were removed, an image enhancement algorithm was used to improve the quality of the images. Finally, grey-scale versions of the images were processed to identify and classify the cracks on the blade surface.

Regarding the processing of drone-based inspection images, the application of deep learning for blade abnormality detection for offshore wind turbines can be an interesting subject. For these algorithms, the important issue is to be fed by tailored and high quality trusted dataset. An open-source dataset of drone-based inspection images has been provided by [17]. A new method for automating the data labelling for drone-based inspection images has been proposed by [18]. The paper has used different deep neural networks architectures such as Inception-V2, and ResNet. Reference [19] has focused on drone-based inspection images and proposed a method for structural health monitoring of wind turbine blades based on Convolutional Neural Network (CNN) classifier. In this paper, the image annotation has been done manually and there were two types of performed binary classification (faulty and normal) with the accuracy above 94 percent, and multi-class classification with nine classes (Sky, Nature and blade, Nature, Lightening damage, Mechanical damage, Tip open, Erosion, Side-erosion and Cracks) and the accuracy above 90 percent. Regarding the blade inspection of offshore wind farms, a formulated and optimized route planning of UAVs has been proposed by [20] in which effect of wind speed, flying range, and flying speed of UAV has been considered. The effectiveness of the proposed method has been simulated and evaluated with Walney wind farm recorded data.

B. Reliability and Availability Assessment of Wind Turbines

Reliability and availability are two important non-functional properties that are increasingly assessed to improve the operation and maintenance of offshore wind farms. Different research efforts have been made for reliability and availability analysis in the wind industry. In [21], the importance of downtime in the offshore deployment of wind turbines and how reliability and availability are linked with downtime were discussed. Alhmoud et al. [22] have discussed the state-of-the-art on the reliability modelling of the wind turbines and addressed reliability modelling techniques, life distributions, reliability testing methodologies, reliability design and severity classifications. Igwemezie et al. [23] have provided the current trend of the offshore wind energies and the requirements. The paper also studied the reliability improvement of the structures in offshore wind turbines. The 127 possible failures on the offshore wind turbine and their combinations have been addressed by [6]. The paper has used the Fault Tree Analysis

(FTA) method for reliability evaluation of floating offshore wind turbines and highlighted the most probable bottlenecks in offshore wind turbine through importance measure. Considering online monitoring data of a system and updating the reliability models is one of hot topics in the filed of reliability and safety engineering. For example, [24] has used Dynamic BN for root cause diagnosis and online reliability evaluation of subsea blowout preventer. Kabir et al. [25] have introduced the concept of complex basic events in Fault Tree with the ability of updating the basic events probabilities based on online monitoring data. Online monitoring data can be also used for safety model repair. Gheraibia et al. [26] has proposed a Support Vector Machine (SVM)-based approach to use online monitoring data and suggest a correction in reliability models like fault tree.

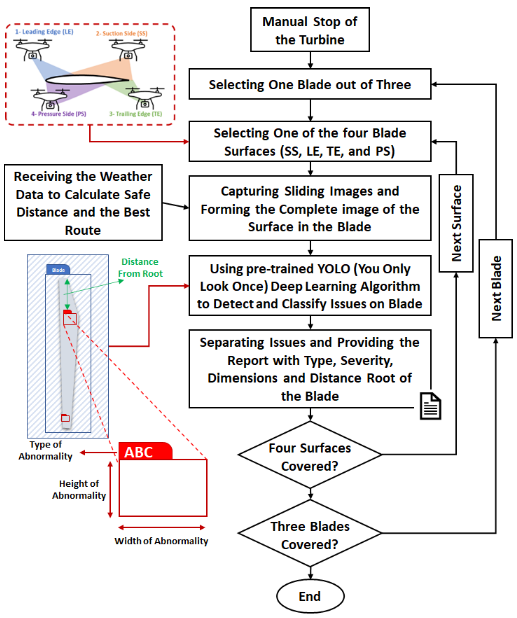

Fig. 1. Image processing flowchart for anomaly detection

III. Proposed Approach

A. Drone Assisted Monitoring and Image Processing

This article assumed that multiple drones will be deployed to monitor the blades of the wind turbines. The drones will inspect the blades and take images of the surface of the blades. The drone-based blade inspection usually takes 60 to 90 minutes and it should cover four areas of each blade's surface including (a) leading edge, (b) suction side, (c) pressure side and (d) trailing edge. For diagnosis of the blades, aspects that can be considered are: I) type of abnormalities such as crack, erosion, fatigue, flaking, etc., II) depth of the abnormalities that is possible when the Laminate exposes, and III) length, width and the distance from root that can be used also to determine the severity of the issue. The images taken by drones are then wirelessly transferred to the onshore facilities for further processing. Note that, drones will communicate with each other for a coordinated inspection of the blades and an optimised transmission of data.

After receiving the blade surface images from the drones via a secure channel, the images are processed to identify the anomalies (e.g. fatigue, cracks) on the surface of the blades. There exist several image processing approaches such as [16], [18] for identifying and characterising the anomalies on the blades. Note that, one can use an existing approach or can even develop a new approach.

Fig. 1 illustrates the flowchart of the anomaly detection process in a wind turbine blade. At the current stage of technology, the turbine needs to be stopped for any type of blade inspection as well as UAV-based inspection. However, having more advanced dynamic positioning may enable UAVs to inspect the blade when the turbine is operational. The procedure would be similar to the procedure of taking a panorama picture with a mobile phone. In this procedure, the UAV should receive some weather data like wind speed and wind direction to adjust the position, calculate the safe distance from the turbine and avoid the collision. Once all images of a surface is taken, an integrated image of that surface of the blade will be constructed. There are different existing algorithms to process an image and find objects or abnormalities inside the image. For instance, YOLO (You Only Look ONCE) is one of the state-of-the-art algorithms for object detection inside an image with high performance (the performance also depends on the quality of the dataset that the algorithm is trained with) [27]. In the next phase, more information such as type, height, width, distance from root and severity of the abnormalities will be provided for each surface of each blade and the process will be continued until all blades and their surfaces are covered. As an example, for erosion and based on [28] it can be possible to calculate the performance loss of the turbine based on dimensions and severity of detected erosion points on the blade.

When the drones are employed to take images, the quality of the images can be affected by several factors. For instance, images can be blurred due to the relative motion between the blades and the camera mounted on the drones. Noise can be introduced to the images due to the harsh operating conditions of drones and noise produced by various surrounding electronic devices. As a result, the decision made based on these images could be affected depending on the quality of the images. For this reason, we have proposed a way to generate confidence in the decision.

Fig. 2 illustrates the proposed procedure. In this procedure, the images taken by each drone will be loaded into the pre-processing unit and then the pre-processed data will be used as the input of the deep learning algorithm as explained earlier. In the next phase, the SafeML tool (a novel open-source safety monitoring tool [29], [30]) is used to measure the statistical difference between new images and the trusted datasets (the datasets that the deep learning model has been trained with and validated by an expert in the design time) to generate the confidence. Having generated the confidence, three scenarios have been considered; (a) if the confidence is very low, then

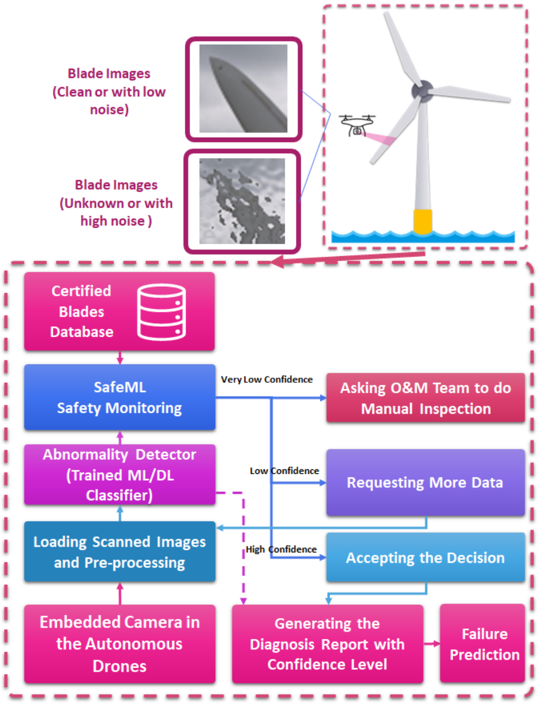

Fig. 2. Failure prediction and confidence evaluation with SafeML

the approach will provide notice for O&M team to do the manual inspection, (b) if the confidence is low, the approach will ask the drone to take more pictures from that specific area, and (c) if the confidence is high, the approach will generate the diagnosis report with addressing the evaluated confidence. In the last scenario, the system will be permitted to proceed with the results autonomously. Note that the threshold for the confidence should be tuned in the design time by an expert. The approach is also capable of providing deep learning explainability and interpretability. Due to brevity, we do not provide a detailed description of this capability.

B. Online Reliability Evaluation

In this phase, it is assumed that the failure behaviour of the blade system is analysed at design time and reliability model(s) are created. A reliability model could be in the form of a fault tree model or a Markov model or a Bayesian network model or any other existing models. At design time, statistical failure probabilities of different events are used for reliability analysis. Now, for online reliability analysis, we utilise the observations provided by the drone-assisted monitoring. At first, we identify which events or parameters within the existing reliability models are observable by the drones. After that, evidence or observations associated with these events or parameters are extracted from the processing of the data shared by the drones. This online monitoring information about the observable events is then provided as updated inputs to the reliability models to get the updated reliability. In this article, we assumed that an event can either be observed to be in some discrete states with certainty or can be observed to be in different states with different probabilities. For instance, at a certain point in time, a component A of a system can be observed to be completely operational or complete failed, i.e., binary observation. On the other hand, the same component can be observed to be said that its failure probability has changed from 0.3 to 0.45, i.e. an increase in prior probability.

IV. Illustrative Example

To demonstrate the proposed approach, we considered the reliability model for blade system failure of offshore wind turbine presented in [31]. In [31], a fault tree model for the blade system failure was presented. In the fault tree model, 16 different basic events (lowest-level causes) are combined using Boolean AND and OR gates to show the causes of the top event *'blade system failure'*. The basic events and their probabilities are shown in Table I. Note that the occurrence probabilities of the basic events shown in the table are hypothetical and used only for illustrative purposes. However, as the proposed approach is generally applicable to any types of system, when the real operational data from a practical system is available they can be used in the same fashion.

TABLE I
Root causes of blade system failure [31] and their assumed probabilities

Event Tags	Name	Probability
BE1	Fatigue of blade root	0.0830
BE2	Blade erosion	0.0458
BE3	Edge delamination of the blade	0.0324
BE4	Manufacturing defects	0.0219
BE5	Loose and broken of connecting bolts	0.0785
BE6	Blade root overload	0.0296
BE7	Excessive displacement	0.0193
BE8	The blades struck by lightning	0.0787
BE9	The vibration of pitch system	0.0196
BE10	The failure of pitch system	0.0116
BE11	Wind vane failure	0.0425
BE12	Anemometer failure	0.0965
BE13	Extreme wind load	0.0590
BE14	The cracks of hub surface	0.0466
BE15	The unbalanced attack angel	0.0294
BE16	Loosening of hubs connection	0.0305

For online reliability analysis of the blade system of a wind turbine, in this article, we have mapped the fault tree of [31] into a BN shown in Fig.3 following the process described in [32]. In this model, the blue coloured nodes are the basic events and their prior probabilities are defined based on the probability values reported in Table I. On the other hand, the green coloured nodes are intermediate events, which are different logic gates in the fault tree. Therefore, the conditional probability tables of these nodes are generated based on the logical behaviour of the logic gates they represent.

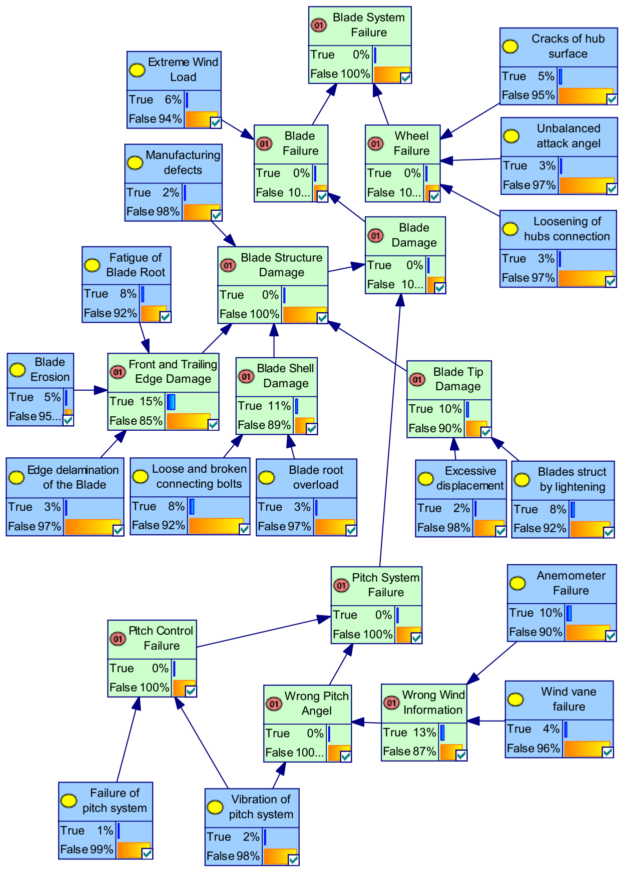

Fig. 3. Bayesian network model of the failure of blade system

Now, for online reliability analysis, we assume that the events BE1: fatigue of blade root, BE2: blade erosion, and BE14: the cracks of hub surface are observable by the drones, and states of other events are not observable by the drones. That means drone-based monitoring can be utilised to provide evidence about the states of these observable events. Based on the data shown in Table I, the probability of the blade system failure is obtained as 2.114E-4.

Table II shows illustrate how probabilistic observations can be used to evaluate the online reliability of the blade system. It was assumed that based on the drone-based monitoring, observations about the changes in occurrence probability of the events can be provided. The change in probability for an event is denoted by P_i^j, which means due to the degradation of the components the occurrence probability of an event i is increased by $j\%$ from its prior probability. We performed experiments with many different combinations of such observations for the three observable events and evaluated the online failure probability accordingly. Due to space limitation, in Table II, only 10 randomly selected cases are reported, where online failure probabilities of the blade system are determined for different levels of increase in failure probability of events BE1, BE2, and BE14. At the same time, to evaluate the individual effect of changes of the failure rate of these events, we performed some experiments by changing the probability of one event at a time while keeping other events' probability unchanged. Result of these experiments is shown in Fig. 4. This figure shows the changes in the online blade system failure probability for a different level of changes to the failure probability of the events BE1, BE2, and BE14, respectively.

TABLE II
ONLINE RELIABILITY OF THE BLADE SYSTEM IN DIFFERENT OBSERVED SCENARIOS

Cases	Basic events			BSFP	% Change (↑↓)
	BE1	BE2	BE14		
C1	P_1^5	P_2^5	P_{14}^5	2.135E-4	0.99% ↑
C2	P_1^{15}	P_2^{15}	P_{14}^{15}	2.179E-4	3.07% ↑
C3	P_1^{25}	P_2^{25}	P_{14}^{25}	2.223E-4	5.16% ↑
C4	P_1^{50}	P_2^{50}	P_{14}^{50}	2.330E-4	10.22% ↑
C5	P_1^{75}	P_2^{75}	P_{14}^{75}	2.439E-4	15.37% ↑
C6	P_1^{10}	P_2^5	P_{14}^{15}	2.178E-4	3.03% ↑
C7	P_1^{20}	P_2^{10}	P_{14}^5	2.137E-4	1.09% ↑
C8	P_1^{15}	P_2^{25}	P_{14}^{15}	2.178E-4	3.03% ↑
C9	P_1^{30}	P_2^{40}	P_{14}^{25}	2.224E-4	5.20% ↑
C10	P_1^{75}	P_2^{20}	P_{14}^{50}	2.331E-4	10.26% ↑

$^*P_i^j$: probability of event i is increased by $j\%$ from its original value reported in Table I

Finally, the grey cells of Table II shows the results of the 10 randomly selected cases of many experiments performed considering the combination of deterministic and probabilistic observations. As can be seen, in each case, for some events deterministic observations are provided while for others probabilistic observations are provided. Also, for each case, the % change in the online failure probability is reported. Form the above illustrations, it can be said that using the proposed approach it is possible to utilise the drone-assisted monitoring to collect the operational states of the components of wind turbines, which can, in turn, be used in the reliability models to calculate online reliability that changes over time due to the changes in the operational states of the components. This kind of online reliability will accurately capture the real operational status of the wind turbine systems, thus can assist in effective maintenance scheduling to improve the performance of the systems both in terms of energy production efficiency and cost of energy.

V. CONCLUSION

This article proposes an approach utilising drone-based monitoring and machine learning for online reliability evaluation of wind turbine systems. Using the proposed approach it is possible to utilise the advantages of the drone-based remote inspection of offshore wind turbines and use the computational power of modern computing facilities to process complex images to facilitate online reliability evaluation. In this current study, due to lack of access to data from a real wind turbine system, we used illustrative example with hypothetical data to demonstrate the proposed approach. In the future, we have

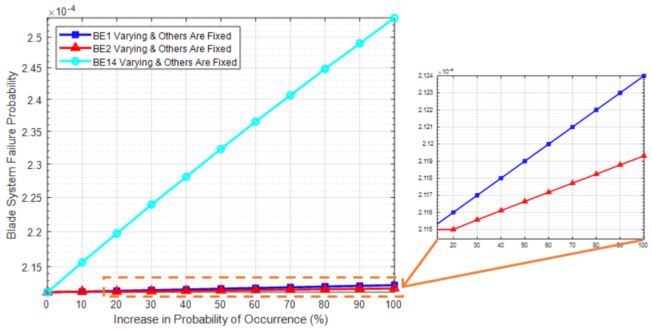

Fig. 4. Failure probability of the blade systems with varying levels of probabilities of events BE1, BE2, and BE14

the plan to verify the effectiveness of this approach through an application to a real system. There are studies related to the reliability and safety evaluation of UAV itself like [33], [34] that can be integrated with our calculation and can be considered as future work.

References

[1] G. Corbetta, A. Ho, I. Pineda, K. Ruby, L. Van de Velde, and J. Bickley, "Wind energy scenarios for 2030," European Wind Energy Association, Tech. Rep., 2015.

[2] M. N. Scheu, A. Kolios, T. Fischer, and F. Brennan, "Influence of statistical uncertainty of component reliability estimations on offshore wind farm availability," *Reliability Engineering & System Safety*, vol. 168, pp. 28–39, 2017.

[3] Technology Innovation Needs Assessment (TINA), "Offshore wind power summary report," Low Carbon Innovation Coordination Group, Tech. Rep., 2012.

[4] R. Martin, I. Lazakis, S. Barbouchi, and L. Johanning, "Sensitivity analysis of offshore wind farm operation and maintenance cost and availability," *Renewable Energy*, vol. 85, pp. 1226–1236, 2016.

[5] J. Dowell, A. Zitrou, L. Walls, T. Bedford, and D. Infield, "Analysis of wind and wave data to assess maintenance access to offshore wind farms," in *European Safety and Reliability Association Conference*, 2013.

[6] J. Kang, L. Sun, and C. G. Soares, "Fault tree analysis of floating offshore wind turbines," *Renewable energy*, vol. 133, pp. 1455–1467, 2019.

[7] S. Adumene and A. Okoro, "A markovian reliability approach for offshore wind energy system analysis in harsh environments," *Engineering Reports*, vol. 2, no. 3, p. e12128, 2020.

[8] T. Adedipe, M. Shafiee, and E. Zio, "Bayesian network modelling for the wind energy industry: An overview," *Reliability Engineering & System Safety*, p. 107053, 2020.

[9] R. Herring, K. Dyer, F. Martin, and C. Ward, "The increasing importance of leading edge erosion and a review of existing protection solutions," *Renewable and Sustainable Energy Reviews*, vol. 115, p. 109382, 2019.

[10] F. P. G. Márquez, A. M. Tobias, J. M. P. Pérez, and M. Papaelias, "Condition monitoring of wind turbines: Techniques and methods," *Renewable Energy*, vol. 46, pp. 169–178, 2012.

[11] J.-K. Lee, J.-Y. Park, K.-Y. Oh, S.-H. Ju, and J.-S. Lee, "Transformation algorithm of wind turbine blade moment signals for blade condition monitoring," *Renewable energy*, vol. 79, pp. 209–218, 2015.

[12] M. Ozbek, F. Meng, and D. J. Rixen, "Challenges in testing and monitoring the in-operation vibration characteristics of wind turbines," *Mechanical Systems and Signal Processing*, vol. 41, no. 1-2, pp. 649–666, 2013.

[13] M. Kapoor and S. Thöns, "Unmanned aerial vehicle benefit assessment for the structural integrity management of wind turbines," in *1st International Conference on Structural Integrity for Offshore Energy Industry*, 2018.

[14] J. Franko, S. Du, S. Kallweit, E. Duelberg, and H. Engemann, "Design of a multi-robot system for wind turbine maintenance," *Energies*, vol. 13, no. 10, p. 2552, 2020.

[15] L. Wang and Z. Zhang, "Automatic detection of wind turbine blade surface cracks based on UAV-taken images," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 9, pp. 7293–7303, 2017.

[16] L. Peng and J. Liu, "Detection and analysis of large-scale WT blade surface cracks based on UAV-taken images," *IET Image Processing*, vol. 12, no. 11, pp. 2059–2064, 2018.

[17] A. Shihavuddin and X. Chen, "Dtu-drone inspection images of wind turbine," 2018.

[18] A. Shihavuddin, X. Chen, V. Fedorov, A. Nymark Christensen, N. Andre Brogaard Riis, K. Branner, A. Bjorholm Dahl, and R. Reinhold Paulsen, "Wind turbine surface damage detection by deep learning aided drone inspection analysis," *Energies*, vol. 12, no. 4, p. 676, 2019.

[19] A. Reddy, V. Indragandhi, L. Ravi, and V. Subramaniyaswamy, "Detection of cracks and damage in wind turbine blades using artificial intelligence-based image analytics," *Measurement*, vol. 147, p. 106823, 2019.

[20] H.-M. Chung, S. Maharjan, Y. Zhang, F. Eliassen, and K. Strunz, "Placement and routing optimization for automated inspection with uavs: A study in offshore wind farm," *IEEE Transactions on Industrial Informatics*, 2020.

[21] S. Faulstich, B. Hahn, and P. J. Tavner, "Wind turbine downtime and its importance for offshore deployment," *Wind energy*, vol. 14, no. 3, pp. 327–337, 2011.

[22] L. Alhmoud and B. Wang, "A review of the state-of-the-art in wind-energy reliability analysis," *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 1643–1651, 2018.

[23] V. Igwemezie, A. Mehmanparast, and A. Kolios, "Current trend in offshore wind energy sector and material requirements for fatigue resistance improvement in large wind turbine support structures–a review," *Renewable and Sustainable Energy Reviews*, vol. 101, pp. 181–196, 2019.

[24] B. Cai, Y. Liu, Y. Ma, Z. Liu, Y. Zhou, and J. Sun, "Real-time reliability evaluation methodology based on dynamic bayesian networks: A case study of a subsea pipe ram bop system," *ISA transactions*, vol. 58, pp. 595–604, 2015.

[25] S. Kabir, K. Aslansefat, I. Sorokos, Y. Papadopoulos, and Y. Gheraibia, "A conceptual framework to incorporate complex basic events in hiphops," in *International Symposium on Model-Based Safety and Assessment*. Springer, 2019, pp. 109–124.

[26] Y. Gheraibia, S. Kabir, K. Aslansefat, I. Sorokos, and Y. Papadopoulos, "Safety+ ai: A novel approach to update safety models using artificial intelligence," *IEEE Access*, vol. 7, pp. 135 855–135 869, 2019.

[27] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 779–788.

[28] A. Sareen, C. A. Sapre, and M. S. Selig, "Effects of leading edge erosion on wind turbine blade performance," *Wind Energy*, vol. 17, no. 10, pp. 1531–1542, 2014.

[29] K. Aslansefat, I. Sorokos, D. Whiting, R. T. Kolagari, and Y. Papadopoulos, "Safeml: Safety monitoring of machine learning classifiers through statistical difference measure," *arXiv preprint arXiv:2005.13166*, 2020.

[30] K. Aslansefat, S. Kabir, A. Abdullatif, V. Vasudevan, and Y. Papadopoulos, "Toward improving confidence in autonomous vehicle software: A study on traffic sign recognition systems," *Computer*, vol. 54, no. 8, pp. 66–76, 2021.

[31] L. Liu, H. Bian, Z. Du, C. Xiao, Y. Guo, and W. Jin, "Reliability analysis of blade of the offshore wind turbine supported by the floating foundation," *Composite Structures*, vol. 211, pp. 287–300, 2019.

[32] S. Kabir, M. Walker, and Y. Papadopoulos, "Dynamic system safety analysis in HiP-HOPS with Petri nets and Bayesian networks," *Safety science*, vol. 105, pp. 55–70, 2018.

[33] K. Aslansefat, F. Marques, R. Mendonça, and J. Barata, "A markov process-based approach for reliability evaluation of the propulsion system in multi-rotor drones," in *Doctoral Conference on Computing, Electrical and Industrial Systems*. Springer, 2019, pp. 91–98.

[34] K. Aslansefat, P. Nikolaou, M. Walker, M. N. Akram, I. Sorokos, J. Reich, P. Kolios, M. K. Michael, T. Theocharides, G. Ellinas *et al.*, "Safedrones: Real-time reliability evaluation of uavs using executable digital dependable identities," in *The 8th International Symposium on Model-Based Safety Assessment (IMBSA 2022)*. Springer, 2022.