Lifetime prediction of wind turbine blades using degradation model considering variable load profiles

Rosmawati Jihin[1], Manh-Hung Do[2], and Dirk Söffker[3]

[1,2,3] *Chair of Dynamics and Control, University of Duisburg-Essen, 47057 Duisburg, Germany*
rosmawati.mat-jihin@uni-due.de
hung.do@uni-due.de
soeffker@uni-due.de

Abstract

Assessment of fatigue damage, classification of system state, prediction of lifetime as well as the extension of maintenance intervals are the challenges in structural health monitoring of wind turbines. Almost all wind turbine parts are subjected to different load combinations due to the variation of wind profiles. The dynamic complexity of wind profiles causes limited ability to define failure thresholds and estimating current health status of the system. Due to numerous factors affecting system operation it is hardly possibly to define solutions calculating degradation and remaining lifetime. Various possible degradation scenarios could be arisen due to a variety of circumstances. Instead of using analytical models, in this contribution numerical (data driven) models with the capability to handle such scenarios and provide more effective degradation prediction are used. The innovation of this work is to implement a modified state machine concept for modeling variable load-induced damage degradation. A newly introduced state machine-based prognostic model is used to enable flexibility in deterioration modeling while concerning the relation between load and system lifetime. In addition to the previous development, here a suitable collection of different loads and wear-dependent basic degradation processes are defined to identify the load-lifetime relation. Using core wear units, the load time series is composed of this units allowing to learn about the effective load-lifetime relation, which is used for training of the state machine model. To observe model applicability, wind turbine blade moments time series data are used. Then, damage degradation for various power-dynamic relations generated using a reference software to train this model and work as reference datasets. Results demonstrate the strong potential of the proposed approach for wind turbine degradation modeling for lifetime prediction.

1. Introduction

The global growth of wind energy sector with installed capacity up to 539 GW in 2017 reported by World Wind Energy Association, signifies a massive installation of wind turbines (World Wind Energy Association, 2018). Large wind turbine structures are complex systems operating non-stop. The combination of complexity in material and design with the operation causes challenges in maintenance processes and element failures which can be hardly anticipated (Leite, Araújo, & Rosas, 2018). This combined factors, trigger discussions among wind farm manufacturers and operators as well as researchers in dealing with tasks associated to advanced maintenance solution known as Prognostic and Health Management (PHM).

The basic goal in PHM is to incorporate safety and reliability of components for fully utilization and evading unnecessary maintenance works (Saxena, Goebel, Simon, & Eklund, 2008). Main methods implemented in robust PHM are known as diagnostics and prognostics aiming to identify the system health status, confronting the faults occurred, and predicting degradation for estimation of remaining useful life (RUL) (Atamuradov, Medjaher, Dersin, Lamoureux, & Zerhouni, 2017). To ensure continuity of wind turbine (WT) operation and preventing unexpected failure besides circumventing costly maintenance, accuracy in RUL prediction is desired.

Predicting lifetime for WT components requires prognostic models capable to deal with uncertainties in data and system complexity. This models commonly treated as add-on to equip more complex management system in assisting decision maker resolving critical production issues (e.g. procurement, maintenance-related, logistic etc.) (Welte & Wang, 2014). It seems to be useful to establish a fault prognosis model able to handle such variations, based on the accessibility of system properties and data availability. According to (El-Thalji & Jantunen, 2015) the field of prognostic modeling can be classified by: data-based (Si, Wang, Hu, & Zhou, 2011), physics-based (Cubillo, Perinpanayagam, & Esperon-Miguez, 2016), and hybrid prognostic (Liao & Köttig, 2014) -based approaches. In most systems, physical properties are hardly attainable, thus data-based models are preferred to represent and interpret damage progression (Yea & Xie, 2015; Jouin, Gouriveau, Hissel, Péra, & Zerhouni, 2016). However, a correlation between model parameters and input and output data need to be determined. The determination can be realized based on axioms and assumptions or can be realized by a data-driven concept first training a model and then apply the learned model. This approach will utilize historical data to predict the damage and/or wear evolution. The correlation between accumulated damage, RUL and end of life (EOL) can be seen in Figure 1. Proper identification of damage progression contributes to high precision in EOL forecasts. Whereas, hybrid prognostic approaches combine advantages and compensate limitations from both approaches to increase accuracy in lifetime prediction (An, Kim, & Choi, 2015). Studies related to this approach merge physic laws and data-based prognostic approaches as a promising concept for degradation state assessment and predicting RUL (Djeziri, Benmoussa, & Sanchez, 2017).

In real situations, damage degradation for WT is stochastic and undeterministic (Nijssen, 2007). This is due to the characteristics of wind dynamics and also to the uncertainties caused by climate conditions (Chandrasekhar, Stevanovic, Corbetta, Dervilis, & Worden, 2017). In this contribution the problem of modeling damage degradation concerning various wind profiles is addressed. Therefore, a newly developed prognostic model is used, here for the first time in combination with a suitably state machine topology, to solve the problem of variable loads here induced by variations due to different wind profiles applied. The identified model will be adapted with WT blade moment data to measure the lifetime prediction performance. In the beginning, classification of wind behavior and related assessment of damage data will be explained in Section 2, followed by state machine-based prognostic modeling discussed in Section 3. Then, results explained in Section 4. Summary, conclusion, and outlook are given in Section 5.

2. VARIABLE LOAD PROFILES

2.1. Wind type classification

The main idea of the new online-applicable approach is to classify the wind dynamics with respect to speed and power allowing to consider different variations in the real measured wind behavior. Variations in wind dynamics and power, produces different damage patterns for each wind profile. Applying a data-driven approach reference data are required for training. Due to missing references here the certified tool MLIFE (NWTC Information Portal, 2015) is used to generate damage-equivalent load (DEL) data as real reference data to be used to obtain EOL, D=1 respectively. Applying the MLIFE approach it is observed that different damage patterns are obtained related to different wind behaviors. The MLIFE program is based on rainflow counting algorithm and load-cycle approach (S-N curve) to compute fatigue damage from time-series data. Details of the procedure are given in (Hayman, 2012).

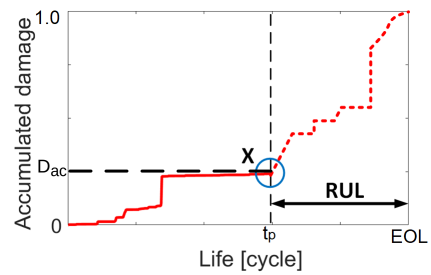

Figure 1. Lifetime prediction based on damage progression starting from point X. D_{ac}: current accumulated damage, t_p: current prediction time

Table 1. Variation of wind profiles based on mean wind speed (WS) and turbulent intensity (TI) for different random seed (RS1, RS2, RS3)

Type	WS (mps)	TI (%)	RS1	RS2	RS3
A	18	12	A1	A2	A3
B	18	16	B1	B2	B3
C	14	12	C1	C2	C3
D	14	16	D1	D2	D3

In this work, without loss of generality four different types of wind are considered in generating DEL according to variations of speed (WS) and turbulent intensity (TI), as shown in Table 1. By combining two levels of wind speed: high (18 mps) and low (14 mps) with distinct portion of turbulent intensity (16 % and 12 %), four wind types are defined. For each wind type, three different stochastic wind profiles (WP1, WP2, WP3) are generated by TurbSim (TurbSim User's Guide, 2012) using different "random seeds" which initialize the pseudorandom number generator. Thus, total of 12 datasets of various wind profiles generated.

2.2. Calculating reference damage data

Four different wind profiles are applied to generate groups of time-series data. Further simulation is carried out by MLIFE to produce damage datasets using rotor blade moments for all wind types. Different damage characteristics can be detected as shown in Figure 2 against cycle time. Obviously, high speed and high turbulent intensity leads to significant damage effects on WT component. Accumulating the damage increments generated by MLIFE, the evolution of damage/wear related to the underlying different wind profiles can be accessed

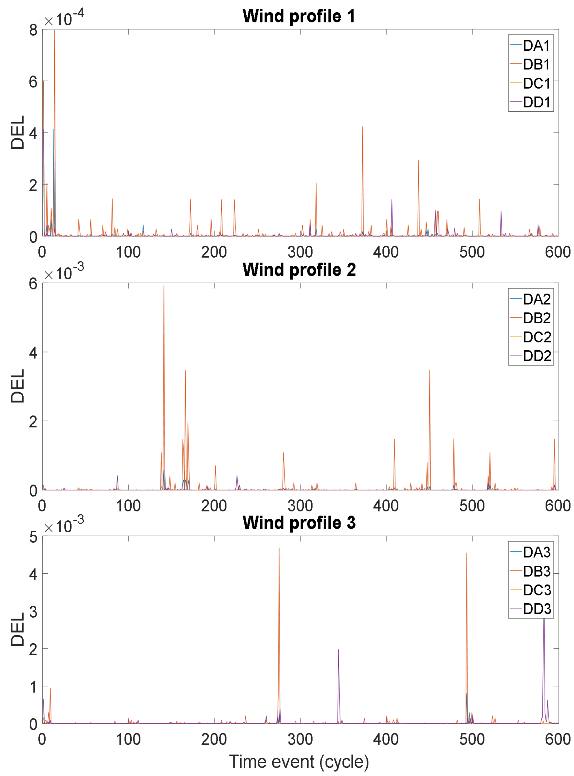

Figure 2. Damage equivalent load (DEL) for variable wind profiles using MLIFE

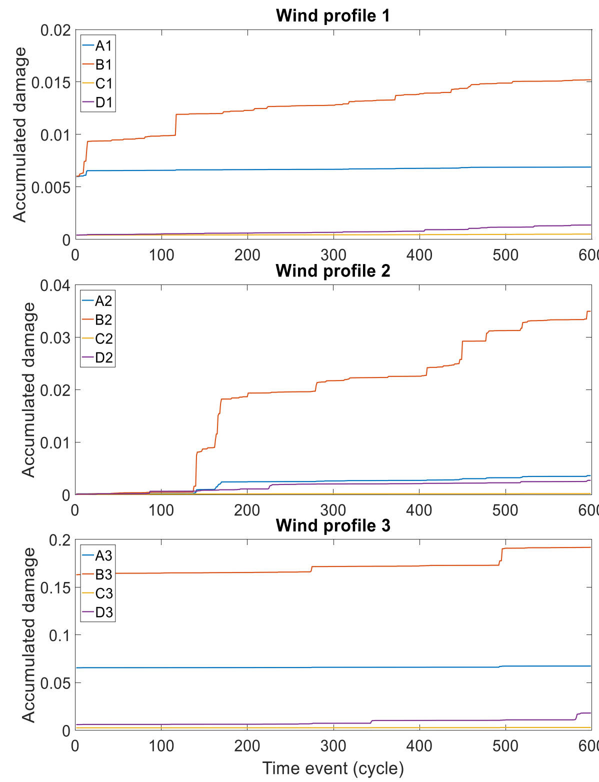

Figure 3. Accumulated damage for variable wind profiles using MLIFE

(Figure 3). This relation between wind profiles and related accumulated damage evolution will be in the next step used for data-driven modeling of the load-damage relation (for loads arbitrarily composed of the underlying load profile patterns). To model the damage for lifetime prediction, a state machine-based model is utilized for reference damage data generation used for RUL prediction. The implementation is comprised of state machine modeling and definition of suitable parameters refining the load-depending model.

3. STATE MACHINE-BASED LIFETIME MODEL

3.1. State machine-based model development

A state machine is used for modeling different states and related transitions of the deterioration process. Each of the state is connected to appropriate lifetime equations related to specific wind profiles. All parameters of the state machine (transition conditions) and of state-related equations (lifetime-related equation parameters) are to be defined numerically. This definition is realized within an optimization loop using NSGA-II (Deb, Pratap, Agarwal, & Meyarivan, 2002) as training process. The approach is firstly presented in (Beganovic & Söffker, 2017). The key property of the method is that the multi-model (here: for lifetime calculation) is understand as a data-driven approach to be defined by data allowing a new quality of flexibility to adapt with problems (topology (Figure 4)) and real systems (data). Here the flexibility is used to cover the variations in power and wind dynamics with respect to WT lifetime.

The states of the assumed topology (Figure 4) are denoted as I, S1, S2, S3, S4 and E. They individually represent different wind types as introduced in Section 2.1. Here, wind speed and turbulent intensity for every time event, designated as WS_i and TI_i, are considered as measured and monitored value. The WS_i and TI_i are used as an input to this model. Lifetime value related to specific wind state are calculated as output. The initial state I defines the starting of WT operation and does not represent any lifetime equation. From this state, as degradation is detected ($DEL > 0$), next possible state depends on transition condition ($f_{0 \longrightarrow 5}$) criteria as listed in Table 2. In the case of $DEL = 1$ the systems fails by definition, which is denoted as state E. The terms TI_1 and TI_2 describe low and high intensity thresholds, while WS_1 and WS_2 are low and high wind speed thresholds. This values are prescribed based on available data and previous knowledge on wind characteristics. Due to the fact that the wind turbine is not operating for WS_i larger than WS_2, four different operation states are to be described. Mathematical equations comprised in each state consists of coefficients assumed as design variables to be defined using optimization. This

Table 2. State definition based on transition conditions

State	Transition condition		
		Turbulent intensity	Wind speed
S1	f_1	$TI_1 \leq TI_i < TI_2$	$WS_1 < WS_i \leq WS_2$
S2	f_2	$TI_1 \leq TI_i < TI_2$	$WS_i \leq WS_1$
S3	f_3	$TI_i \geq TI_2$	$WS_1 < WS_i \leq WS_2$
S4	f_4	$TI_i \geq TI_2$	$WS_i \leq WS_1$

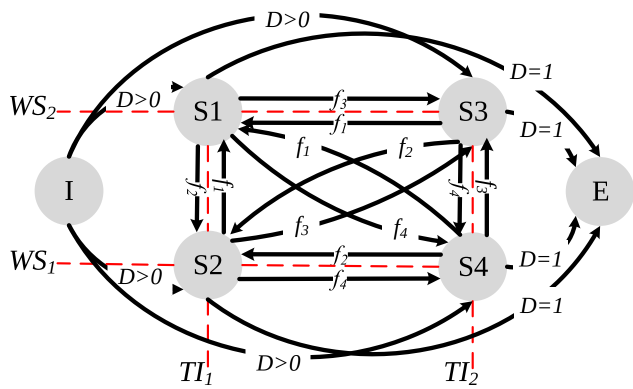

Figure 4. State machine topology for lifetime modeling based on wind characteristics

process will be explained next.

3.2. Parameter definition

Realizing the data-based prognostic model, suitable parameters are essential to accommodate the unknown system properties and uncertainties. The incomplete information from historical data related to system degradation and failure progress should also be addressed by the parameters. The identified model consists of multi states representing different deteriorating levels. All parameters need to be defined. The model associated with training data used to determine appropriate coefficients by including parameters optimization in the prognostic process flow, demonstrated in Figure 5. This approach defines the values simultaneously by imposing the state machine model into optimization loop.

Using measured data (damage data) according to wind characteristics (wind profiles) the best parameters for all states has to be defined. Here optimization is used, so that the optimized parameters explains together with the assumed topology the measured behavior. This process is considered as an offline procedure. By integrating the determined parameters in an online process, the damage progress can be predicted and reliable RUL is calculated. The preciseness of RUL also depends on training data provided for optimization algorithm.

3.3. Optimization using NSGA-II

The optimization scheme provides an optimal solution for parameter values to refine the machine state model. It will enhance the model performance estimation and initiate the state using prior knowledge of system health. The complete model in this case is defined by state describing equations and related coefficients. The transitions defining parameters are also defined by training via optimization. In the beginning, state was justified using wind profile data followed by evaluation of damage-lifetime relation configured by NSGA-II. This process apply the actual methods of NSGA-II algorithm. The prescribed objective for the optimization is to minimize the variance between estimated and real (here: MLIFE-based simulated) training datasets. Within specified iteration, the optimal parameters acquired by NSGA-II are stored and forwarded for the test process. This procedure enable validations on applicability of the identified parameters to the other datasets that having different wind characteristics.

In this work, the WT is considered to be exposed to four types of wind profiles as stated in Table 1. The known wind profiles were used to train and test model, to define optimized parameters for each load-lifetime state equation. Five group datasets were chosen for training and test based on Monte Carlo experiments as listed in Table 3. This method basically applied randomness in data sampling and makes it adaptive to variations of numerical computation (Sun, Zuo, Wang, & Pecht, 2012). Two dataset groups are used for training with different arrangement of data. First training group (denoted as single-typed data) comprised of dataset A1, B1, C1, and D1. It features similar wind characteristics (stationary state for each dataset) and constant increment of damage for each lifecycle. While, second group (denoted as combined-typed data) combining data from four wind profiles and structured them into new datasets namely G1, G2, G3, and G4. The restructured data based on combinations are shown in Table 4. Instead of using constant wind profiles for all event, this new datasets (combined-typed dataset) expressing variability (state changing) in wind behavior, as presented in Figure 6. Training model with various wind profile combinations are able to improve parameters more thoroughly. In addition, the deviation errors (as prescribed in NSGA-II) must be minimized and very small so that all the optimized parameters (from this training procedure) can be accepted for the test or on-line process. Further discussion is highlighted in the next section.

4. RESULTS AND DISCUSSIONS

Evaluation of predictions are important to justify the quality and applicability of the proposed approach. This work performed two steps of evaluation: first, procedure used in training process was evaluated and second, performance of lifetime prediction being assessed. The discussion which train-

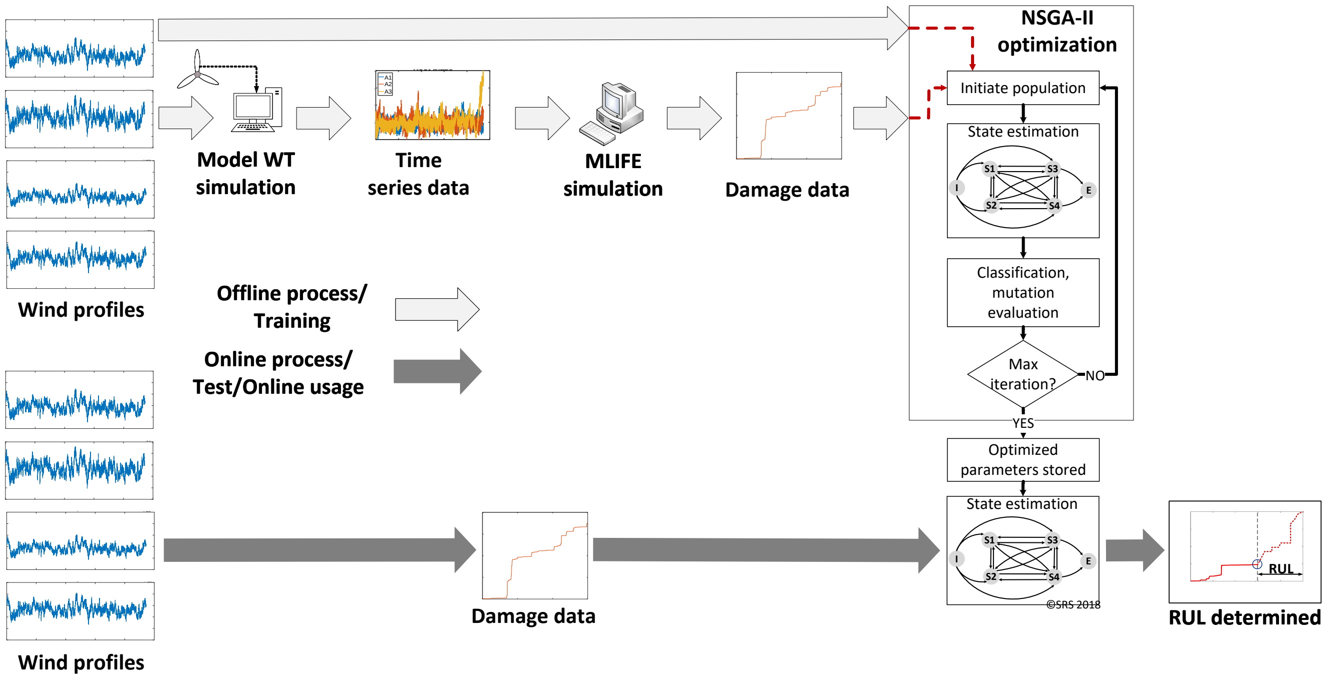

Figure 5. Prognostic process

Table 3. Variation of training procedure

Training procedure	Training dataset	Test dataset
Single-typed data	A1, B1, C1, D1	A2, B2, C2, D2 A3, B3, C3, D3
Combined-type data	G1, G2, G3, G4	G5, G6, G7, G8

Table 4. Combination of restructuring damage data

Group sign	**G1**	**G2**	**G3**	**G4**	**G5**	**G6**	**G7**	**G8**
Data 1	A1	B3	A2	C1	D2	A3	B1	C2
Data 2	B1	A3	B2	D1	A2	C1	A1	D2
Data 3	C1	C3	C2	B2	B3	D2	D1	A2
Data 4	D1	B2	D2	A2	C3	C3	B3	C1
Data 5	A2	D2	B1	C2	A1	A1	C3	D3
Data 6	C2	C2	C1	D3	D1	B2	A2	B1

ing approach (training 1: using single-typed data or training 2: using combined-typed data) able to provide desired findings is crucial to obtain accurate RUL prediction. To identify best training procedure, prediction from testing datasets, as listed in Table 3, were compared based on three metrics: Root Square Error (RSE), Mean Square Error (MSE), and Absolute Error (ABE). Comparison between training approach 1 and training approach 2 executed to identify which approach capable to produce most optimal parameters to refine load-lifetime equations (state equations). By using eight datasets (A2, B2, C2, D2, A3, B3, C3, D3) from single-typed wind behaviour and four combined-typed datasets (G5, G6, G7, G8) accuracy of the model prediction are assessed. All datasets used for calculating the performance metrics consist of 600 segments wind profile, where each segment describes approximately 1 second of simulation. Figure 7 shows the comparison of two training approaches based on three performance metrics. Here, summation deviation errors between simulated damage and predicted damage (calculated using respective state equation) for each test datasets are used to measure the accuracy. These results are based on 600 segments data point, where each segment represents 1 second simulation data. Using training 1-approach, datasets A3 and B3 produced high errors compared to other test dataset. Some other datasets like B2 and G6 also show large errors in their load-lifetime prediction. By testing the same datasets using training 2-approach, impressive errors reduction can be obtained for all datasets. The errors tend to zero. This is expected as the pattern of wind variations using combined-type data extensively cover all the four states during training. This includes that the applied data set(s) are more representative, so the resulting optimized data model represents better (more optimal) parameters to be used for test. It can be concluded that optimized parameters gained using training 2-approach best fit the state equations since the damage calculated produced better finding compared to training 1-approach. In general it should be noted that the data applied cover only a very small segment in time and therefore the absolute errors are small.

It can be seen from Figure 8 that the selection of state based on wind behavior of G5 dataset is capable to predict almost perfect estimation of lifetime with deviation error less than

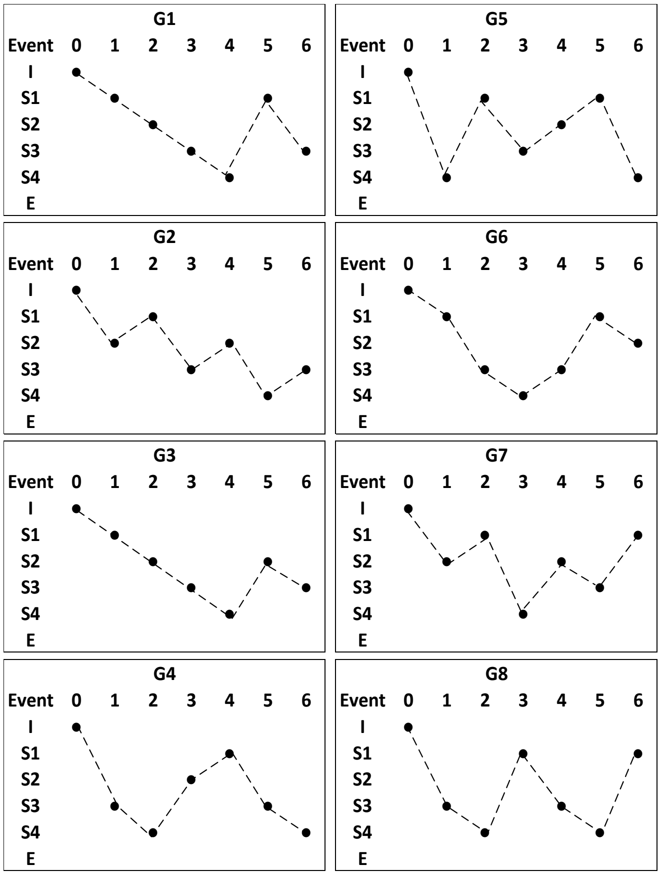

Figure 6. Trellis diagram representing wind profile behavior based on combined data listed in Table 4

0.01 percent. The performance was also measured based on accuracy of EOL prediction, which also related to RUL. Since the future wind profile is unknown, this work assumes that it will be similar like historical behavior. Thus, degradation is predicted to perform stationary linear increment using damage data calculated by the proposed approach. The final measured data considered as the beginning of prediction time. From that point, the predicted damage is accumulated until the value reach 1. Time point when the accumulated damage reach 1 denoted as EOL, and can be used to estimate the RUL. Predicted EOL are compared with EOL from MLIFE and the percentage of accuracy shown in Figure 9. High precision prediction gained by all dataset with average estimation around 99.83%. This provides evidence that the proposed state machine model is capable to account wind profile variations in prognostic lifetime process using the available data.

Despite the very good results obtained two aspects should be noted which actually restricts the applicability of the new approach: First training and test is based on nearly realistic wind profile data, but representing using a limited and (in this contribution: equal) set of wind variations (good enough to show

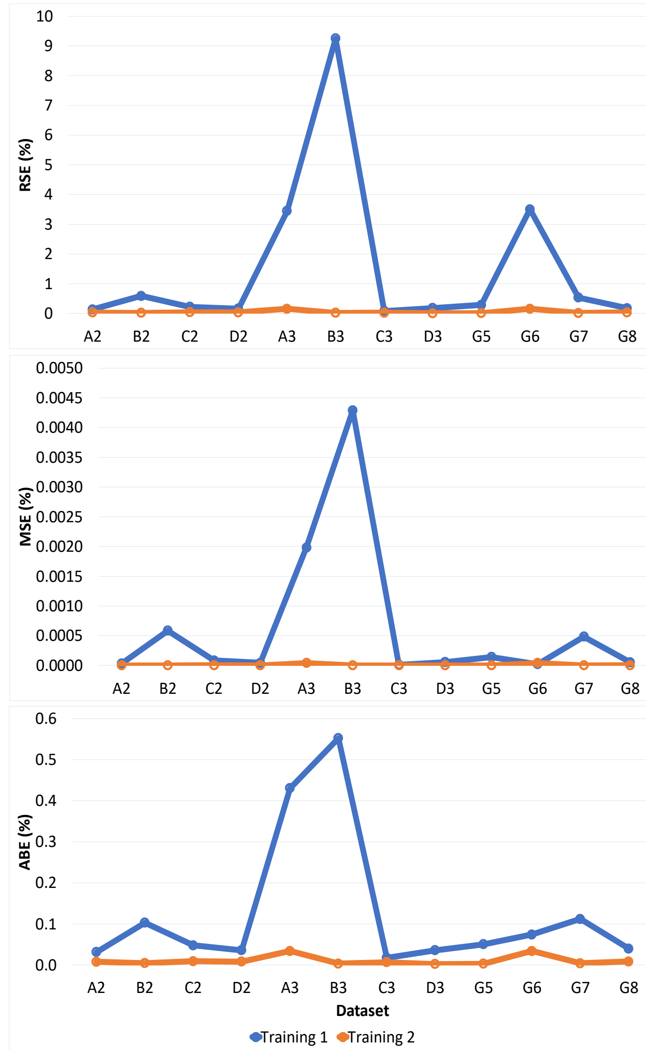

Figure 7. Comparison of RSE, MSE and ABE for various testing dataset based on different training approach

the method but possibly not good enough to cover the reality). The variation is realized in a stochastic sense. In reality it may be the case that the real wind profile combinations are exactly not stochastic and show a strong and unknown bias. In this case training and test data representations are not similar, so the approach may not work so perfect. Secondly the reference data for RUL are generated by using MLIFE, which is based on linear damage accumulation rules. This makes it also easier to adapt the reference behavior due to training. Real RUL data are not based on such assumptions.

This may explain the obtained good results, nevertheless the newly introduced scheme should also be able to cover more realistic cases. Further studies based on more realistic RUL reference data will show the real quality of the approach developed.

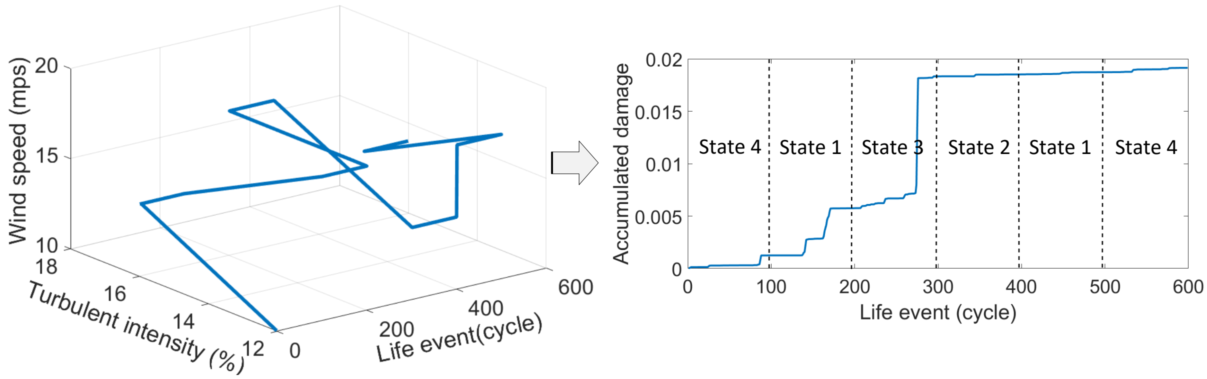

Figure 8. State selection and lifetime-damage prediction using G5 wind profile data

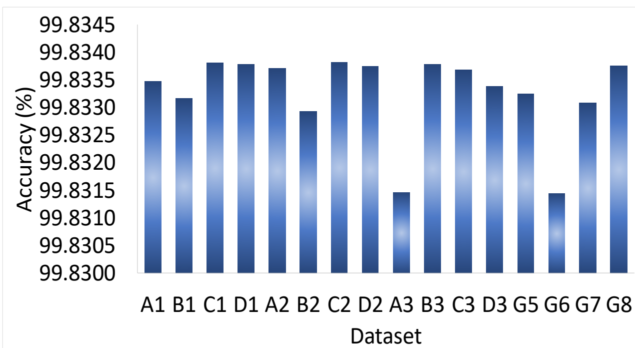

Figure 9. Accuracy of EOL prediction for various datasets

5. SUMMARY, CONCLUSION, AND OUTLOOK

The variations of wind profiles contributed to the complex of degradation modeling and reduction of accuracy in lifetime prediction. To tackle this issue, a newly developed prognostic model is applied for RUL estimation. The key challenge in this context is to handle various wind characteristics. In this work, the wind profile is assumed to change randomly between state 1, 2, 3 and 4. Implementing state machine approach as a base of prognostic modeling allows flexibility in model selection which can be used to estimate future degradation. By integrating this approach into the optimization loop of NSGA-II, parameters refining the load-lifetime equations for each state are successfully defined during training phase. This optimized parameters are tested using reference damage datasets for various combination of wind characteristics. It is observed from metric accuracy (Figure 7), that the errors of deviation for simulated and calculated damage tend to zero for all datasets. The degradation progress signified that the estimated RUL and EOL converges to the measured (in this case simulated) ones with average prediction accuracy 99.83%. This is also indicated by almost very good generation of predicted degradation path and extremely low prognostic errors (less than 0.01 percent for G5 dataset). In this application a first step to tackle the problem of unknown but characterizable load profile is shown from a principle as concept. For the evaluation within a real application the approach has to be applied and optimized for conditions up to D=1, also integration load conditions which does not perfectly fulfil the classes used for training. However, investigation using other type of stochastic data or nonlinear degradation may require further research.

ACKNOWLEDGMENT

The research reported in this paper are partly supported by the Ministry of Higher Education Malaysia through In-service Scholarship received by first author and by the Vietnam International Education Development (VIED) Scholarship received by second author for their Ph.D. study at the Chair of Dynamics and Control, UDE, Germany.

REFERENCES

An, D., Kim, N. H., & Choi, J. H. (2015). Practical options for selecting data-driven or physics-based prognostics algorithms with reviews. *Reliability Engineering and System Safety*, *133*, 223–236.

Atamuradov, V., Medjaher, K., Dersin, P., Lamoureux, B., & Zerhouni, N. (2017). Prognostics and Health Management for Maintenance Practitioners - Review, Implementation and Tools Evaluation. *Int. Journal of Prognostics and Health Management*, *8*, 1–31.

Beganovic, N., & Söffker, D. (2017). Remaining lifetime modeling using State-of-Health estimation. *Mechanical Systems and Signal Processing*, *92*, 107–123.

Chandrasekhar, K., Stevanovic, N., Corbetta, M., Dervilis, N., & Worden, K. (2017). On the Structural Health

Monitoring of Operational Wind Turbine Blades. In *11th Int. Workshop on Structural Health Monitoring 2017* (pp. 2522–2529).

Cubillo, A., Perinpanayagam, S., & Esperon-Miguez, M. (2016). A review of physics-based models in prognostics: Application to gears and bearings of rotating machinery. *Advances in Mechanical Engineering*, *8*, 1–21.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, *6*(2), 182–197.

Djeziri, M. A., Benmoussa, S., & Sanchez, R. (2017). Hybrid method for remaining useful life prediction in wind turbine systems Hybrid Method for Remaining Useful Life Prediction in Wind Turbine Systems. *Renewable Energy*, 1–15.

El-Thalji, I., & Jantunen, E. (2015). A summary of fault modelling and predictive health monitoring of rolling element bearings. *Mechanical Systems and Signal Processing*, *60*, 252–272.

Hayman, G. J. (2012). *MLife Theory Manual for Version 1.00* (Tech. Rep. No. October).

Jouin, M., Gouriveau, R., Hissel, D., Péra, M. C., & Zerhouni, N. (2016). Degradations analysis and aging modeling for health assessment and prognostics of PEMFC. *Reliability Engineering and System Safety*, *148*, 78–95.

Leite, G. d. N. P., Araújo, A. M., & Rosas, P. A. C. (2018). Prognostic techniques applied to maintenance of wind turbines: a concise and specific review. *Renewable and Sustainable Energy Reviews*, *81*, 1917–1925.

Liao, L., & Köttig, F. (2014). Review of hybrid prognostics approaches for remaining useful life prediction of engineered systems, and an application to battery life prediction. *IEEE Transactions on Reliability*, *63*, 191–207.

Nijssen, R. R. (2007). Fatigue Life Prediction and Strength Degradation of Wind Turbine Rotor Blade Composites. (Dissertation, Delft University), 1–242.

NWTC Information Portal. (2015). *Accessed 11.12.2017.* Retrieved from `nwtc.nrel.gov/MLife`

Saxena, A., Goebel, K., Simon, D., & Eklund, N. (2008). Damage Propagation Modeling for Aircraft Engine Prognostics. In *Int. conference on prognostic and health management* (pp. 1–9).

Si, X. S., Wang, W., Hu, C. H., & Zhou, D. H. (2011). Remaining useful life estimation - A review on the statistical data driven approaches. *European Journal of Operational Research*, *213*, 1–14.

Sun, J., Zuo, H., Wang, W., & Pecht, M. G. (2012). Application of a state space modeling technique to system prognostics based on a health index for condition-based maintenance. *Mechanical Systems and Signal Processing*, *28*, 585–596.

TurbSim User's Guide. (2012). National renewable energy laboratory. , 1–87.

Welte, T. M., & Wang, K. (2014). Models for lifetime estimation: an overview with focus on applications to wind turbines. *Advances in Manufacturing*, *2*, 79–87.

World Wind Energy Association. (2018). *Wind Power Capacity reaches 539 GW, 52.6 GW added in 2017.*

Yea, Z. S., & Xie, M. (2015). Stochastic modelling and analysis of degradation for highly reliable products. *Applied Stochastic Models in Business and Industry*, *31*, 16–32.

BIOGRAPHIES

Rosmawati Jihin received B.Eng.(Hons.) degree in Mechanical Engineering in 2004 and M.Eng. in Mechanical Engineering in 2014, both from University Malaya, Malaysia. She was working as a lecturer in Mechanical Engineering Department of Ungku Omar Polytechnic, Malaysia. Currently, she is pursuing Ph.D. at the Chair of Dynamics and Control, U Duisburg-Essen in the area of structural health monitoring.

Manh-Hung Do received B.Sc. degree in Automation and Control in 2009 and M.Sc. in Automation and Control in 2011, both from Hanoi University of Science and Technology, Vietnam. He was working as a lecturer in School of Heat Engineering and Refrigeration, Hanoi University of Science and Technology, Vietnam. Currently, he is pursuing Ph.D. at the Chair of Dynamics and Control, U Duisburg-Essen in the area of wind turbine control.

Dirk Söffker received the Dr.-Ing. degree in mechanical engineering from the University of Wuppertal, Wuppertal, Germany, in 1995 and the Habilitation license in Automatic Control/Safety Engineering from the same university in 2001. Since 2001 he has held the Chair of Dynamics and Control with the Engineering Faculty, U Duisburg-Essen, Germany. Prof. Söffker is a Member of the German Society of Applied Mathematics and Mechanics (GAMM) and IEEE. His current research interests include elastic mechanical structures, modern methods of control theory, safety and reliability control engineering of technical systems, and cognitive technical systems.