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Resilience Informed Performance Assessment of Infrastructure Systems

Jianjun Qin
Assistant Professor, Dept. of Civil Engineering, Aalborg University, Esbjerg, Denmark

Michael H. Faber
Professor, Dept. of Civil Engineering, Aalborg University, Aalborg, Denmark

ABSTRACT: Over the recent decade increased research efforts have been directed on the modeling of resilience of infrastructure systems in their context, i.e. as socio-technical systems. The present paper presents a generic resilience model framework for the support of design and integrity management of such systems. The starting point is the general system representation framework by JCSS (2008) with special consideration of the modeling of uncertainties and dependencies. Furthermore, the evolution of the performance, together with the expected value of benefits and losses, as well as the capacity of infrastructure systems over time is described. On this basis the resilience modeling is formulated considering the performances of and the interactions between infrastructure systems, the organization responsible for integrity management and regulations. Finally, an example is presented considering the modeling and analysis of the resilience of one wind turbine park for the purpose of optimizing resilience management. Parameter studies are presented illustrating how the resilience performance may be optimized by means of adjusting the reliability of subsystems as well as through allocation of income for coverage of costs of future inspections, maintenance and renewal works. Moreover, it is illustrated how performance relevant indicators such as the down time and the stock keeping of essential spare parts can be assessed through the proposed resilience analysis framework.

1. INTRODUCTION

Resilience of systems has attained significant interest over the last 2-3 decades across the natural, social, human and engineering sciences, see e.g. Derissen, et al. (2011), Linkov, et al. (2014), Qin, et al. (2017) and Faber, et al. (2018). Whereas, within the different sciences, the systems of interest are of rather diverse characteristics, there is general agreement with respect to the concept. Resilience is commonly understood as an aggregate characterization of systems encompassing their ability to maintain their main modes and levels of services, to develop and mobilize resources to adapt to and sustain disturbances over time.

Research on resilience within the engineering sciences has been focusing on the modeling of how engineered systems are able to sustain one given disturbance scenario, how, to which extent and by when the organizations managing them are able to reestablish their functionalities and not least the losses associated with disruptions and rehabilitations. Knowledge in this respect greatly facilitates the understanding of how engineered systems in their organizational context may be designed and managed optimally for given individual events of disturbances, such as historical earthquakes, flood and storm events. With this basis, the statistical characteristics of the mentioned system performances with respect to all relevant, and in principle unknown individual disturbance events, may be assessed by probabilistic modeling and analysis.

In Faber, et al. (2017), system resilience is addressed from a more holistic perspective, addressing not only one (possibly random) event of a given disturbance scenario but rather all possible time histories of disturbance events over the lifetime of the systems, and thereby facilitates the modeling of the generation of the time-variant net benefit provided by systems. This formulation in turn makes it possible to model the capacity of the systems over time and thus opens up to represent and assess resilience failure events from a probabilistic perspective. System resilience failure events are thus defined as the events where the available accumulated capacities of the system are exhausted by the demands associated with the disturbance events - where capacities and demands may relate to economy, human resources and environmental resources.

In the present paper we build on the formulation of system resilience model from Faber, et al. (2017) and adapt this to address resilience informed performance assessment of infrastructure systems. In Section 2, the general framework of system modeling presented by JCSS (2008) is introduced first and the system representation of infrastructure systems will be introduced briefly considering uncertainties and dependencies. Section 3 outlines an analytical framework for the probabilistic modeling and analysis of resilience of infrastructure systems. It is assumed that the considered hierarchical system is managed by an owner/operator organization and the resilience of the system is modelled and assessed with respect to different decision alternatives; while the decision alternatives that satisfy the resilience requirements may be identified and based on which the performance of the infrastructure systems can be assessed. In Section 4, an example is provided to illustrate the resilience analysis and the subsequent performance assessment of a wind turbine park composed by ten wind turbines and the influences of the preparedness level, target design reliability and the accumulated capacity are investigated.

2. PERFORMANCE OF INFRASTRUCTURE SYSTEMS

A general system modeling framework is presented by the Joint Committee on Structural Safety (JCSS) (JCSS (2008)) in the context of risk assessment. In the framework, the system performance is changed by the exposure, while the consequence is divided into two categories, i.e. direct consequence and indirect consequence. Direct consequences comprise the losses directly caused by damage and failure states of the constituents of the system, while indirect consequences relate to the propagation failure events and functionality and service provision losses.

Concerning the damage and failure state of the constituents of the system, Failure Mode and Effect Analysis (FEMA) or Failure Tree Analysis (FTA) might be applied to the assessment, see e.g. Tavner, et al. (2007) and Sørensen and Toft (2010); while in many cases, especially for the constituents of structural systems, the relevant failure modes and the failure event may be represented in a probabilistic analysis through unions and intersections of individual failure modes represented by limit state equations. At system level, as soon as the performance of the constituents are assessed, the dependencies between the performance necessitate to be addressed. For example, when a wind turbine park is considered, two levels of the dependencies may be taken into account, i.e. turbine level dependency (the dependency between the performances of individual wind turbines) and subsystem level dependency (the dependency between the performances of subsystems). Wind turbines located in the same wind turbine park, are generally subject to similar environmental loads and natural hazard events, e.g. similar intensities of wind, waves and wind waves for offshore wind turbines, while also operational demands on e.g. generators and gearboxes are dependent. Moreover, wind turbines within one wind turbine park are subject to the same general strategies with respect to monitoring, control, maintenance and renewals. At subsystem level, subsystems of one wind turbine work together and the change of the condition state of one or more subsystems may cause that of the other subsystems in a cascading manner. The scheme for the representation of systems of wind turbine parks considering two levels of dependency is shown briefly in Figure 1.

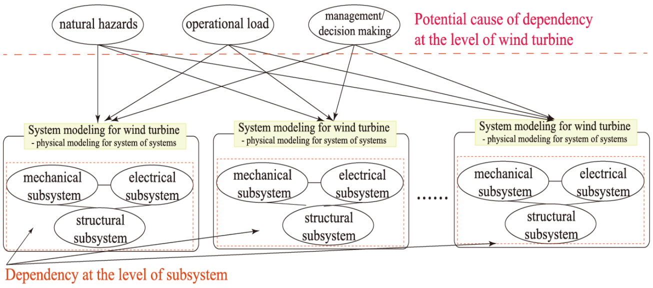


Figure 1: System representation of wind turbine parks considering two levels of dependency.

3. RESILIENCE INFORMED PERFORMANCE ASSESSMENT OF INFRASTRUCTURE SYSTEMS

The resilience of engineered systems is considered by Faber, et al. (2017) from a service life perspective and the evolution of service provision and associated benefit generation are modeled together with the capacities of the system (organizational, economic and/or ecological) over time. Resilience failure is defined as the event that one or more of the capacities are exceeded by demands and/or the consequences of disturbances.

The resilience model presented in Faber, et al. (2017) proposes the economic capacity of a system to be generated by accumulating a fixed percentage $\chi\,\%$ of the economic output (benefit) provided by the service provision of the system. It is assumed that a startup capacity is available at time $t=0$. This is taken as $\chi\,\%$ of the expected value of the annually generated benefit considering all relevant disturbance events over the service life of the system. Disturbance events may cause damages to the system and correspondingly the benefit generation will be reduced for a period of time. The immediate drop in the benefit rate after a disturbance event may be noticed to relate directly to system reliability and robustness. The accumulated reserves will decrease to support the recovery activities.

Following Faber, et al. (2017), the limit state function of the event of resilience failure at time t could be expressed as:

$$g_{\mathrm{RF}}(t)=r_r\left(\mathbf{X}(t),\mathbf{a}\right)-s_r\left(\mathbf{X}(t),\mathbf{a}\right) \tag{1}$$

where r_r and s_r are functions representing the capacity and the demand of the system at time t, respectively. The demand is in principle any event with the potential to reduce the capacity of the system, typically referred to as disturbances. It should however, be noted that not only sudden and large consequence events are of relevance, but also effects of e.g. slowly evolving degradation and lack of efficiency in integrity management may be critically important. $\mathbf{X}(t)$ is a vector of random variables which in general depend on time and $\mathbf{a}$ is a vector containing all decision alternatives which may affect the resilience performance of the system. The probability that this function g_{RF}, for the first time during a considered reference period (service life), attains a negative value represents the probability of resilience failure of the system, $P_{\mathrm{RF}}\left(\mathbf{X}(t),\mathbf{a}\right)$.

As soon as the probability P_{RF} is provided for all the possible vectors of decision alternatives $\mathbf{a}$, the optimal decision may be identified correspondingly based on a minimization of the probability of resilience failure or even the maximization of the total benefit. Based on the identification of the optimal decision $\mathbf{a}$, the performance of the infrastructure system, together with its consequences, can be assessed.

In the following section, the resilience modeling introduced here is utilized to address the resilience analysis of wind turbine parks. The system representation of wind turbine parks is formulated as a two level hierarchy of systems as shown in Figure 1. It is assumed that the considered hierarchical system is managed by an owner/operator organization and the resilience performance of the system is modelled and assessed with respect to different decision alternatives with respect to levels of design reliability and preparedness. The evolution of benefit and reserve with time represented here is applied for the modelling of individual wind turbines directly; while the evolution for the wind turbine park is provided, together with other different perspectives such as down time during the service life and the stock keeping of essential spare parts, based on that for the individual wind turbines.

4. EXAMPLE

In the following, resilience assessment of one wind turbine park with ten identical wind turbines, model GE 1.5 SLE, is considered. The configuration and operational data of this model can be found in Mendoza, et al. (2015). The service life for the individual wind turbines is set to be 30 years. For illustrational purpose, each wind turbine is composed by three different subsystems, namely the electrical subsystem (such as generator and electrical control), the mechanical subsystem (such as mechanical brake and gearbox) and the structural subsystem (such as main shaft and rotor blade). The structural subsystems are assumed to be exposed to environmental load disturbances such as wind and waves, L_H . The capacity of a structural subsystem, in this regard, r_H , is modelled by a log-normal distribution random variable. The expected value and the coefficient of variation of r_H are 1 and 0.3 respectively. The limit state function representing the failure event of individual structural subsystems with respect to the environmental load disturbances is:

$$g_H = z_1 r_H - L_H \tag{2}$$

where z_1 is design parameter calibrated to comply with the requirements to the target reliabilities of wind turbines. The occurrences of the environmental disturbance events are assumed to follow a Poisson process with annual rate $\lambda_H = 3$. The intensities of disturbance events acting on each wind turbine within the wind turbine park is modelled by a random vector $\mathbf{I}_H$ with constituents assumed to be Gumbel distributed. The intensities of the disturbance $\mathbf{I}_H$ acting on different wind turbines in this park at a given time are correlated with correlation coefficient ρ_{I_H} as 0.8. The expected values and the coefficients of variation of the intensity I_H , i.e. $E[I_H]$ and $COV[I_H]$, are equal to 1 and 0.4, respectively. The electrical subsystems and mechanical subsystems have their respective capacities to withstand the operational demands. It is assumed that the failure rate with respect to the operational load of the subsystems of all the wind turbines of this park, defined as the reciprocal of the mean time between failure (MTBF), lies on the constant part of a bathtub curve and remains constant over time. Furthermore, the performance of each subsystem is described by a homogeneous Poisson process (HPP) model, see e.g. Tavner, et al. (2007) and Sørensen and Toft (2010) for reference. That is, the long-term effect of the subsystem capacity such as fatigue is not considered in the present investigation. It is assumed that all the wind turbines in the wind turbine park are designed and built simultaneously. They are subject to the same demands and disturbances and managed in accordance with the same management strategy. It is further assumed that the failure of the electrical subsystem or the mechanical subsystem of one wind turbine may produce extra loads on its structural subsystem and make it fail also. Wind turbines with two different levels of target reliability are considered in the investigation here and the corresponding values of the relevant parameters relevant to the reliability of structural subsystems and the reliability of the other two types of subsystems are provided in Tables 1 and 2respectively. The two groups of values of MTBF defined in Table 2are taken from Tavner, et al. (2007) corresponding to the statistical analysis of the 10-year data of the reliability of wind turbines in Denmark and Germany respectively.

The benefit generated by the individual wind turbines is realized by their power generation. All the wind turbines in the park are the same model and it is assumed that they have same power generation function, which describes the relation between the power generation and wind speed. Following the discussion in e.g. Jin and Tian (2010), Lydia, et al. (2014) and Royal Academy of Engineering (2014), the power generation G by individual wind turbine with uncertainties is considered as:

$$G = \begin{cases} 0 & v \le v_{\text{in}} \\ \frac{1}{2}\rho\pi R^2 C_p v^3 + \varepsilon & v_{\text{in}} < v \le v_{\text{rated}} \\ G_{\text{rated}} & v_{\text{rated}} < v \le v_{\text{out}} \\ 0 & v > v_{\text{out}} \end{cases} \quad (3)$$

where v is the wind speed, while v_{in}, v_{out} and v_{rated} represent the cut-in speed, cut-out speed and rated speed respectively. G_{rated} is referred to as the rated power and treated as a constant for a specified model. ρ is the air density, R is the radius of the rotor and C_p is called as the power performance coefficient, which will vary with wind speed v. The variable ε represents the uncertainty in the estimation of the power generation. The values of the radius of the rotor, the cut-in speed, the cut-out speed, the rated speed, the rated power of model GE 1.5 SLE, provided in the performance test report Mendoza, et al. (2015), are considered as constants in the investigation here. Also the air density ρ is considered as constant in the whole wind farm and it is set to be 1.00kg/m^3, while the power performance coefficient C_p, which varies with wind speed, takes the data directly from the onsite test presented in Mendoza, et al. (2015). It is assumed that the variable ε follows a Normal distribution with mean value and standard deviation as 0 KW and 2 KW respectively as the suggestion by Jin and Tian (2010). For simplicity, it is further assumed that any two turbines in this park are separated far from each other and the interaction between them in the power generation is ignored.

Table 1: Parameters relevant to the design reliability of structural subsystems with different target levels.

Target level	Reliability calibration to environmental load		Conditional failure probability of the structural subsystem given the failure of the electrical or the mechanical subsystem of the same wind turbine
	Probability of failure due to environmental load $\Pr(g_H < 0)$	z_1	
Low	1.2×10^{-2}	2.5	0.3
High	1.1×10^{-3}	3.5	0.1

Table 2: Values of MTBF of electrical and mechanical subsystems with different target levels of design reliability (unit: hours).

Target level	Electrical subsystem	Mechanical subsystem
Low	25708	90472
High	450643	1236712

Table 3: Replacement cost for different type of subsystems.

Type of subsystems	Replacement cost
Electrical subsystem	0.3
Mechanical subsystem	0.2
Structural subsystem	1

In the following investigations, wind scenario 2 presented in Kusiak and Song (2010) is considered here as the random daily wind direction and maximal wind speed of the park. It is assumed that wind speed v (at a given location, height and direction) follows a Weibull distribution and wind speeds at different locations share the same Weibull distribution across this park. The wind turbines turn with the change of the wind direction so that the wind direction is considered to have no influence on the power generation but only the values of the parameters of Weibull distribution of wind speed.

Given a disturbance event, each subsystem has two condition states, i.e. 'survival' and 'failure'. Failure of any subsystem of one wind turbine implies total loss of service from that turbine. If one wind turbine performs well (no subsystem fails), it generates electricity in accordance with design specifications as its anticipated service. The benefit per unit time *(year) provided by one wind turbine is assumed to be equal to the ratio of the average power generation by the maximal daily wind speed during the year to its rated power, i.e. 1500KW for the model GE 1.5 SLE. It is assumed that the subsystems are replaced upon their failure and the replacement costs of different types of subsystems are given in* Table 3.

The evolution of the benefit generated from one wind turbine for a particular realization of a disturbance event is illustrated in Figure 2. The benefit generation is reduced to zero at the time of the disturbance. ΔT_1 represents the period from the realization of the disturbance till the service of the wind turbine has been re-established and it is modelled by a log-normal distributed random variable. Two preparedness levels of the operator organisation to deal with the damage caused by the disturbance event are considered, i.e. low and high, which affect the rapidity of the recovery. The expected value $E[\cdot]$ and the coefficient of variation $COV[\cdot]$ of ΔT_1 vary with the preparedness levels and the cause of the failure of the wind turbine, i.e. the failure of the subsystems leading to the loss of service of the wind turbine. A high preparedness level implies relatively small expected value of the recovery period and also low coefficient of variation; while a low preparedness level has the opposite effect. Replacement activities for the structural subsystems are generally rather involving and take a long time compared with other subsystems. Simultaneous failure of more than one subsystem may take place in which case the recovery period of the wind turbine is assumed to be equal to that of the subsystem with the longest recovery period. The probabilistic model for the recovery period is provided in Table 4. The evolution of the benefit from the entire wind turbine park is simply the sum of the benefits generated from the individual wind turbines.

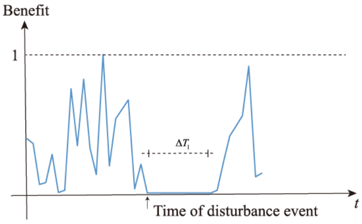


Figure 2: Illustration of the reorganization and recovery of the benefit of a wind turbine for a particular realization of a disturbance event.

Table 4: Probabilistic model of the recovery period ΔT_1 with respect to the type of subsystems that stops the turbine to work as well as preparedness level.

Distribution	Preparedness level	Expected value (unit: month)			COV
		Structural subsystem	Electrical subsystem	Mechanical subsystem	
Log-normal	Low	1	1/3	1/3	0.2
	High	1/3	1/9	1/9	0.1

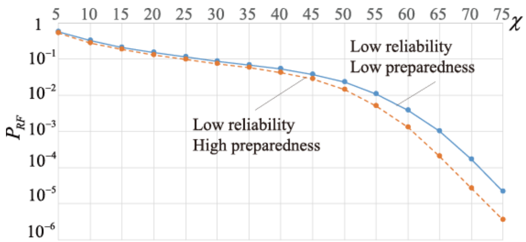


Figure 3: Annual probability of resilience failure with the variation of the percentage χ %.

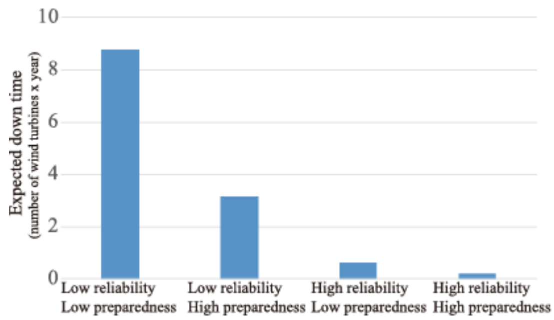


Figure 4: Expected down time of the park within the 30-year service life.

The economic capacity at the beginning of the service life is assumed equal to a percentage χ% of the expected value of the accumulated benefits over the service life of the park. In the following, resilience of the wind turbine park is analyzed to investigate the influence of the target level of the design reliability for environmental load disturbances and the operational load, preparedness level and the percentage χ%. Two different target levels of design reliability of wind turbines and two different preparedness levels are considered here. The resilience is quantified by the probability of resilience failure (the exhaustion of the economic capacity accumulated by the system of time) within the service life in dependency of χ %.

Monte Carlo simulations are applied to assess the annual probability of resilience failure P_{RF} . The annual probability for the case with low target design annual reliability of wind turbines for different values of χ % is estimated, and the results are illustrated in Figure 3, each based on $1\text{x}10^4$ Monte Carlo simulations. The logarithm of the resilience failure probability falls with the increase of χ%. As χ% increase the difference between the resilience failure probabilities become more pronounced. For the case with high target design annual reliability, the resilience failure probability is only apparent when χ% is 5% - in which case the annual probability of resilience failure is between $1\text{x}10^{-3}$ and $1\text{x}10^{-2}$. This case is not shown in Figure 3.

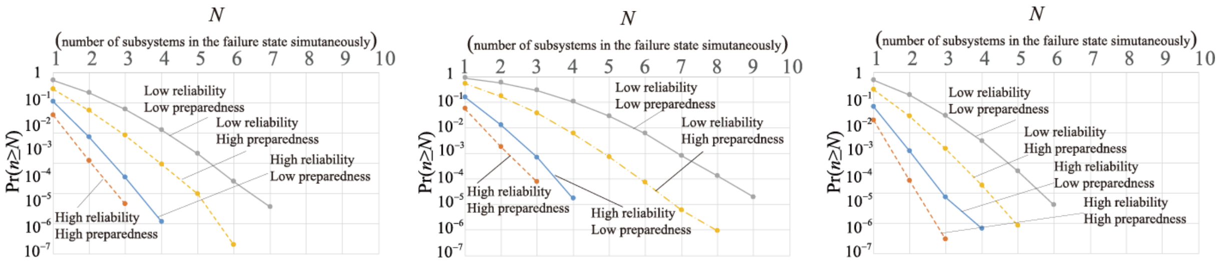
The proposed resilience model may also be applied to assess the reliability of energy provision. In this respect, the down time during the service life and the probability distribution of the number of different types of subsystems in the failure state simultaneously are investigated with these four scenarios. The results of expected down time from $1\text{x}10^4$ simulations are illustrated in Figure 4. It can be seen that both the increase of design reliability and the increase of preparedness level reduce the down time; while the effect of target level of design reliability is great compared with the preparedness level. The complimentary cumulative distribution of the number of different types of subsystems in the failure state simultaneously is obtained also from $1\text{x}10^4$ numerical simulations to provide the basis for the stock keeping of essential spare parts and the results are provided in Figure 5. The interval with large number of subsystems is generally not covered by the curves because no failure of such number of subsystems is captured to have the failure state simultaneously in these simulations.

5. CONCLUSIONS

In the present paper, a previously developed framework for system resilience modelling and analysis is adapted to resilience informed performance assessment of infrastructure systems. Following Faber, et al. (2017), the resilience is modelled from a service life perspective to measure whether the capacity of infrastructure systems could sustain the damage by the disturbances and the subsequent repair activities. Based on the resilience model, the decision alternatives that could satisfy the resilience requirements would be identified and correspondingly, the performance of infrastructure systems would be assessed.

The general idea of the approach is illustrated on the resilience analysis of one wind turbine park with ten wind turbines. The uncertainties associated with the performance of individual wind turbines, the different levels of dependency within the performance of the parks as well as the damage of different types of subsystem that cause the loss of production of wind turbines are captured in the analysis of the time evolution of benefit and losses of wind turbines over time. From the example, it is demonstrated that decisions on the target reliability of the design of individual wind turbine with respect to disturbance events and operational load may be assessed and optimized to reach requirements in terms of resilience. The framework allows decision making on how much of the utility generated by the system should be kept in reserve as well as what level of preparedness should be achieved to ensure sufficient capacity to recover from the potential disturbances during the service life. Moreover, the performance relevant indicators of the park, such as the down time and the stock keeping of essential spare parts are readily quantified within the framework.

The resilience modelling presented is general, however, for illustrational purpose, the system representation of wind turbine parks presented here is rather simplistic. Further detailing accounting for fatigue crack growth and corrosion as well as the measurement of the Value of Information (VoI) from the health monitoring of different part of subsystems can and should be included in further developments.



(1) electrical subsystems *(2) mechanical subsystems* *(3) structural subsystems*

Figure 5: Complimentary cumulative distribution of number of different types of subsystems in the failure state simultaneously.

6. REFERENCES

Derissen, S., Quaas, M. F., and Baumgärtner, S. (2011). "The relationship between resilience and sustainability of ecological-economic systems." *Ecological Economics*, 70(6), 1121-1128.

Linkov, I., Bridges, T., Creutzig, F., et al. (2014). "Changing the resilience paradigm." *Nature Clim. Change*, 4(6), 407-409.

Qin, J., Sansavini, G., and Faber, M. H. (2017). "Probabilistic Modelling of Robustness and Resilience of Power Grid Systems." *The 2nd International Workshop on Modelling of Physical, Economic and Social Systems for Resilience Assessment*, Joint Research Centre (European Commission), ed., European Commision, Ispra, Italy, 23-35.

Faber, M. H., Miraglia, S., Qin, J., et al. (2018). "Bridging resilience and sustainability - decision analysis for design and management of infrastructure systems." *Sustainable and Resilient Infrastructure*, 1-23.

Faber, M. H., Qin, J., Miraglia, S., et al. (2017). "On the Probabilistic Characterization of Robustness and Resilience." *Procedia Engineering*, 198(Supplement C), 1070-1083.

JCSS (2008). "Risk Assessment in Engineering - Principles, System Representation & Risk Criteria." The Joint Committee on Structural Safety (JCSS).

Tavner, P. J., Xiang, J., and Spinato, F. (2007). "Reliability analysis for wind turbines." *Wind Energy*, 10(1), 1-18.

Sørensen, J. D., and Toft, H. S. (2010). "Probabilistic Design of Wind Turbines." *Energies*, 3(2), 241-257.

Mendoza, I., Hur, J., Thao, S., et al. (2015). "Power Performance Test Report for the U.S. Department of Energy 1.5-Megawatt Wind Turbine." National Renewable Energy Laboratory (NREL), Golden, Colorado, 52.

Jin, T., and Tian, Z. (2010). "Uncertainty analysis for wind energy production with dynamic power curves." *2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems*, IEEE, Singapore, Singapore, 745-750.

Lydia, M., Kumar, S. S., Selvakumar, A. I., et al. (2014). "A comprehensive review on wind turbine power curve modeling techniques." *Renewable and Sustainable Energy Reviews*, 30, 452-460.

Royal Academy of Engineering (2014). *Wind Energy*, London, UK.

Kusiak, A., and Song, Z. (2010). "Design of wind farm layout for maximum wind energy capture." *Renewable Energy*, 35(3), 685-694.