Resilience Informed Integrity Management of Wind Turbine Parks

Jianjun Qin * and Michael Havbro Faber

Department of Civil Engineering, Aalborg University, 9220 Aalborg, Denmark
* Correspondence: jq@civil.aau.dk; Tel.: +45-9940-7694

check for updates

Abstract: A novel framework for resilience modeling of wind turbine parks is proposed in support of optimization of decisions on asset integrity management. The concept of resilience originating from natural and social sciences is adapted here to facilitate the joint optimization of decision alternatives related to design, with decision alternatives addressing organizational performance. The generic probabilistic systems representation framework by the Joint Committee on Structural Safety (JCSS) (2008) is utilized to establish a scenario-based modeling of how different types of disturbances may lead to damages and failures of systems and sub-systems of wind turbine parks, together with associated direct and indirect consequences. Special emphasis is directed on the consistent probabilistic representation of the uncertainties and the stochastic and causal dependencies within the wind turbine park system. The framework facilitates the identification of optimal asset integrity management decision alternatives that fulfill given requirements to resilience. The potentials associated with the use of the framework are highlighted by an example considering a wind turbine park with ten identical wind turbines, with each modelled as a system of mechanical, electrical, and structural sub-systems. The resilience performance characteristics of the wind turbine park, such as the expected value of generated service life benefits, the expected value of production down time, and the probability of resilience failure are modelled and quantified such as to support the ranking of decision alternatives relating to the design of the wind turbine sub-systems, the level of organizational preparedness, the percentage of the generated service life benefits to be kept to ensure sufficient economic capacity to deal with future disturbances, and the stock-keeping of essential spare parts.

Keywords: resilience; decision optimization; reliability; life-cycle performance; wind turbine park

1. Introduction

The success of wind energy as a renewable substitute for traditional fossil-based fuels is key for reduction of CO_2 equivalent emissions and sustainable development in general. Significant advances in the use of wind energy concepts have been achieved over the several decades in many countries. The share of wind power for electricity supply in Denmark, for example, has been increasing steadily since 1980. The share reached 10% in 1999 and by 2008 it increased further to close to 20%. By 2015, the wind penetration reached an impressive 42% of the total Danish power supply. The pressing need and also demand for wind energy significantly drives the wind turbine technology, and within the last few decades the size, capacity, and complexity of individual wind turbines and wind turbine parks have increased substantially. However, at the same time, the risks associated with the operation of wind turbine parks have also increased. As outlined in previous work [1,2], the successful operation of wind turbine parks is challenged by not only variability of available wind but also by frequent changes in legal requirements and regulatory policies. By 2030 it is estimated [1] that by 2030 the European wind energy sector will protect up to 6% wind power capacity against market risk through support

schemes. The other 94% is divided into being partially exposed (67%) and totally exposed (27%) to the energy market.

Wind turbine parks ultimately serve sustainable societal development. To succeed in this, however, a number of constraints must be fulfilled. Among these the requirement for efficiency in service life performance and reliability of electricity production play major roles. The efficiency in service life performance relates not only to the income generated by the produced electricity but also to the costs of design, construction, operation, renewals, and decommissioning. Efficiency enhances economic feasibility and competitiveness to the benefit of the wind energy sector and the owners and operators of wind turbine parks, but is also essential for the impact of wind energy on sustainable societal developments. The reliability of electricity production is key for efficiency. Only when the reliability is well understood and under control is it possible to integrate wind energy into the electricity market optimally. The buyers of the wind generated electricity must know to which extent electricity is available in terms of production volume, as well as its temporal variability.

Significant research has been conducted to improve the knowledge on the performances of wind turbines and on how these may be managed efficiently. Methods of statistics and probability as a means for consistent representation of available information and as basis for decision analysis, as outlined in previous work [3], greatly facilitate this. To this end, several databases containing long-term performance records have been established [4–7]. Such databases are utilized in previous work [8–11] for failure analysis of wind turbine sub-systems and wind turbines. Further probabilistic models of wind turbine systems were formulated and applied to analyze the reliability of wind turbine systems [12–14]. Operational wind profiles were formulated and analyzed probabilistically [15] for three selected locations in south-east Nigeria, and a thorough review of probabilistic models can be found in previous work e.g., [16,17], together with propositions for new models. Besides providing the basis for energy production, the wind is also a major cause of events of deterioration and failures for wind turbine systems [18]; other hazards, such as earthquakes, ship collisions, ice forces, and scour, are reported in previous work e.g., [19–22].

Efficiency and reliability over the life-cycle of engineered systems, (e.g., wind turbines, wind turbine park grids, monitoring and control systems, etc.) depend not only on engineered systems as they are realized, but rather, and maybe even more so, on their governance. Legal requirements, policies for the regulation of the energy market, codes and standards for the design and operation of the engineered systems, and not least, the strategic, operational, and tactical management by the owners or operators are of crucial importance in this context [1,23]. Integrity management of wind turbine parks is substantially challenged by the fact that such systems, in general, are of high complexity, comprising a large number of interacting constituents and sub-systems of different types, distributed over considerable geographical areas with environmental conditions and performances associated with large uncertainties [24]. To meet this challenge, in the context of integrity management, it is necessary to establish adequate quantitative representations of their performance characteristics, enhancing decision support as well as transparent communication of implications of choices among decision alternatives with stakeholders of both technical and non-technical backgrounds. To facilitate this, a new paradigm for asset integrity management must be introduced with due consideration of the interactions and the back-couplings between decisions on governance and management and the benefits and risks of different metrics associated with their life-cycle performances; concepts of systems resilience appear adequate to facilitate this.

Over the last 2–3 decades, research in resilience of systems has attained significant interest across the natural, social, human, and engineering sciences [25–28]. Despite the inherent differences between the systems addressed within the different sciences, there appears to be general agreement on the understanding of the concept of resilience. Various definitions of resilience may be found in the literature, as introduced in previous work [29], including:

1. Pimm [30]: Resilience is the time it takes until a system that has been subjected to a disturbance returns to its original mode and level of functionality.
2. Holling [31]: Resilience is the measure of disturbance that can be sustained by a system before it shifts from one equilibrium to another.
3. Cutter et al. [32]: Resilience is the capacity of a community to recover from disturbances by their own means.
4. Bruneau et al. [33]: Resilience is a quality inherent in the infrastructure and built environment; by means of redundancy, robustness, resourcefulness, and rapidity.
5. National Academy of Science (NAS) [34]: Resilience is a system's ability to plan for, recover from, and adapt to adverse events over time.

The definitions by Pimm [30] and Holling [31] originate from the research on ecological systems. In the case of wind turbine parks, the definition of Holling [31] might translate to what is normally associated with structural or mechanical resistance. The definition by Pimms [30] on the other hand puts the focus on the time of normal operation that might be lost due to disturbances, and would for wind turbine parks relate to down time and loss of production. The definition by Cutter et al. [32], which originates from social sciences, highlights the importance of governance or management capacity, which for wind turbine parks might be related to the operators capacity for strategy (design and strategies for assets integrity management), operation (logistics, monitoring and control), and tactical (preparedness) planning of the owners and operators. Safety culture, foresightedness, and ability to learn and adapt from experience are of key importance in this context. The definition by Bruneau et al. [33] underlines the significance of performance characteristics of engineered systems, which may be achieved or strengthened by typically engineering design decisions (redundancy and robustness, as well as easy and fast maintenance). Finally, the definition of the National Academy of Sciences (NAS) [34] synthesizes the foregoing definitions and highlights the importance of a long-term perspective (service life of the wind turbine parks) and the self-reliance quality also included by Cutter et al. [32], which emphasizes that the owner or operator should be able to successfully manage the wind turbine parks over all phases of their service lives without help from the outside. In the following, the definition of resilience from Faber et al. [29] is adapted: "resilience is an aggregate characterization of systems encompassing their ability to maintain their main modes and levels of services, and on their own to develop and mobilize resources to adapt to and sustain disturbances over time".

Most research on resilience within the engineering sciences until now has focused on; (i) the modeling of the ability of engineered systems to sustain a predefined disturbance scenario; (ii) how, to what extent, and by when the organizations managing them are able to reestablish their functionalities; and not least (iii) the modelling of the losses associated with disruptions and interventions. 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 infrastructures or cities subjected to historical earthquakes, floods, and storm events. In a previous study [29] it was proposed to add "event-oriented" focus to this traditional engineering, a holistic service life perspective where all possible and unknown disturbances that might occur and affect the system's performance characteristics over the life times of the systems are accounted for. This novel framework facilitates for the modeling of: (i) the generation of the net benefit provided by systems over time; (ii) the development of the capacities of systems (e.g., in terms of economy, human resources,

and environmental resources) over time; and (iii) the probabilistic modelling of resilience failure as the event that one or more of a system's capacities are exhausted by the losses imposed by disturbances.

In the present contribution, a framework and approach for resilience informed systems asset integrity management is presented based on previous work [29,35], and the system resilience analysis framework initially presented in another study [28]. The performance characteristics of wind turbine parks and the consequences associated with different decision alternatives are represented, modelled, and assessed probabilistically, so as to facilitate for decision optimization by means of the Bayesian decision analysis [36].

Following the probabilistic systems modelling framework proposed by the Joint Committee on Structural Safety (JCSS) [37], Section 2 presents the general approach for the representation of the life-cycle performances of wind turbine parks. A key feature in the proposed system representation is to draw attention to and facilitate for the identification of scenarios and decisions affecting service-life performances. These relate to operational wind profiles, natural hazards, operational loads, and management decisions on design, operation, and maintenance. Two levels of dependencies within wind turbine park systems are accounted for in the proposed system representation, namely dependencies at the sub-system level (mechanical, electrical, and structural) and at the individual wind turbine level. In Section 3, an analytical framework is proposed for the probabilistic modeling and analysis of resilience of general infrastructure systems. This framework is introduced to facilitate for the joint consideration of service life benefits, risks, and resilience characteristics of systems evolving over time, including governance, regulatory, social, infrastructure, environmental, and geo-hazard sub-systems. Based on the proposed resilience modelling framework, the service-life performances of wind turbine parks may be assessed and the acceptable region of decision alternatives with respect to design, strategies for inspection and maintenance planning, repairs, and renewals satisfying given resilience requirements may be identified, thus facilitating optimal service-life oriented asset integrity management. In Section 4, Value of Information (VoI) analysis from Bayesian decision analysis is introduced as a means for consistent quantification of the benefit associated with structural health monitoring. Finally, in Section 5, an illustration of the application of the presented framework is provided through an example considering resilience informed decision optimization of asset integrity management for a wind turbine park. A probabilistic system representation is formulated accounting for design decision alternatives, uncertainties associated with disturbance characteristics, the operational wind profile, failure occurrences, consequences of failure, and recovery preparedness. Each individual wind turbine in the considered wind turbine park is modelled as a system of systems. Monitoring of system characteristics during operation as an instrument for resilience and risk management is introduced and VoI analysis is utilized to assess the feasibility of monitoring strategies. Based on the example results, a discussion of potentials and needs for further research and development is provided and suggestions for the application of the framework are highlighted.

2. System Representation of Wind Turbine Parks

The general probabilistic systems modeling framework presented by JCSS [37] is utilized as the basis for the probabilistic representation of wind turbine parks. The framework represents the probabilistic characteristics of systems based on scenarios of events starting with exposure events, over damages and failures to system constituents and associated direct consequences, and ending in indirect consequences. Direct consequences are generally related to losses directly caused by damages and failure states of the constituents of the system. Indirect consequences relate to the effects of propagation of failure events, as well as losses of functionality and service provision.

In the modeling of consequences, both generation of benefits and losses are explicitly accounted for. The considered benefits are assumed to be directly associated with the total amount of electrical power generated by the wind turbine park. The losses are associated in principle with any damage or failure event of the system, including the cost associated with repairing or replacing the damaged sub-systems or components, as well as associated losses of electrical power generation.

Failure Mode and Effect Analysis (FEMA) or Failure Tree Analysis (FTA) might adequately be applied in support of identification of potentially relevant damage and failure states (scenarios) of the systems and sub-systems of individual wind turbines (see previous work [12,13] for reference). Generally, the relevant scenarios may be represented probabilistically through logical systems comprised by unions and intersections of individual failure mode events represented by limit state equations [38]. Further, when considering wind turbine parks as systems comprised by interconnected individual wind turbines, two levels of dependencies must be taken into account, namely, dependencies between individual wind turbines (wind turbine level), and dependencies between the different sub-systems (mechanical, electrical, and structural) comprising individual wind turbines (sub-system level). Wind turbines located in the same wind turbine park are generally subject to similar operational wind profiles and hazard events, e.g., for offshore wind turbine parks, similar operationally related wear and degradation, and similar intensities of extreme wind events. Moreover, wind turbines owned or operated by the same organization and operated within the same wind turbine park are subject to the same management strategies with respect to design, monitoring, control, maintenance, and renewals. At the sub-system level, mechanical, structural, and electrical sub-systems jointly provide the functionality. Damage or failure of one or more of the sub-systems may cause failure of the other sub-systems in a cascading manner. The suggested representation of wind turbine parks as systems of sub-systems, considering the two levels of dependencies described in the foregoing, is illustrated in Figure 1.
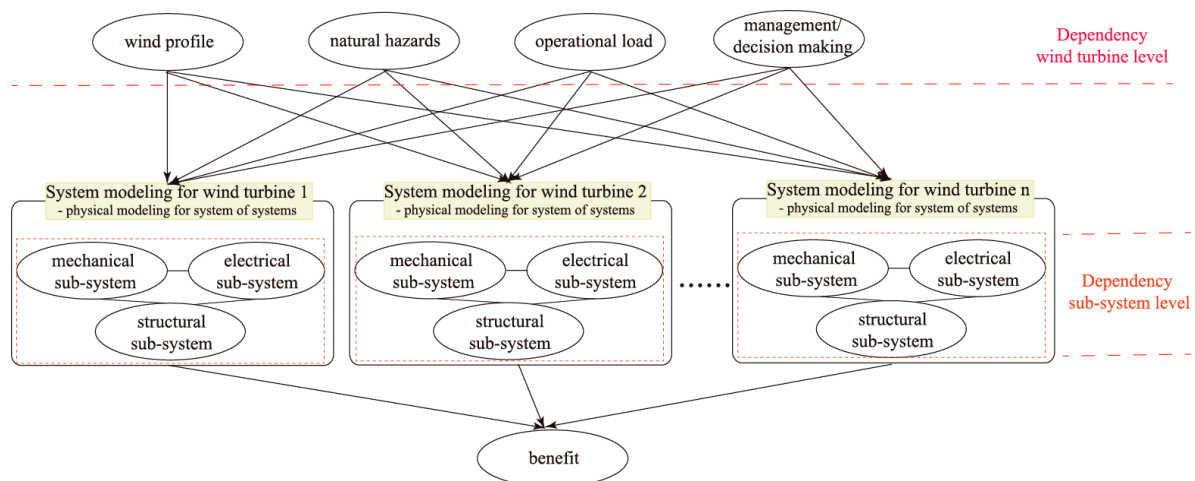

Figure 1. System representation of wind turbine parks considering dependencies between individual wind turbines and dependencies between sub-systems within individual wind turbines (adapted from previous work [35]).

The service life benefits for the wind turbine park system b may be expressed as:

$$b = b(\mathbf{X}(t), \mathbf{a}) \tag{1}$$

where $\mathbf{X}$ is a vector of causally related and stochastically dependent random variables affecting the performances of wind turbine parks, as shown in Figure 1, generally depending on time t, and $\mathbf{a}$ is a vector containing all relevant decision alternatives that may be applied to manage the resilience performances of the system; as discussed in previous work [39], not all of the variables included in $\mathbf{X}(t)$ are necessarily random. The appropriate formulation of $b(\mathbf{X}(t), \mathbf{a})$ depends strongly on the particular decision context and its probabilistic analysis, as required in order to support the ranking decision alternatives for asset integrity management problems, is in general not trivial by means of highly efficient probabilistic analysis tools. However, the application of Monte Carlo simulation, though not necessarily very fast, provides for both robust and precise analyses.

3. Resilience Modeling for Infrastructure Systems

As the basis for the modeling of resilience of wind turbine parks, the probabilistic resilience model proposed in previous work [29] is utilized, as seen in Figure 2. The wind turbine park, as a system comprising individual wind turbines, produces electricity, which in turn is exchanged for money. The income provides for the generation of economic capacity of the system (broken lines in Figure 2) by accumulating a fixed percentage $\chi\%$ of the income (full lines in Figure 2). It is assumed that the system from its beginning at $t = 0$ is allocated a startup capacity. In the following, the start-up capacity is modelled as $\chi\%$ of the expected value of the service life benefit generated by the system, accounting for the effects of all disturbance events that may cause damage to the system and correspondingly implies costs of interventions and reductions in the generated benefits. In Figure 2, two different realizations of service life benefit generations are illustrated. The green line corresponds to a realization resulting in a resilience failure, i.e., where a disturbance event results in damages that are so severe that the required investments to re-establish the functionality of the system exhausts the accumulated economic capacity. The realization shown with a blue line illustrates a history of benefit generation, where disturbances occur but do not result in resilience failure. For illustration purposes, in Figure 2 it has been assumed that the generation of benefit is constant over time under normal operations. For wind turbine parks, for which the benefit generation depends directly on the strongly time varying availability of wind, this is, however, generally not the case, as will be addressed in more detail in the example shown in Section 5.
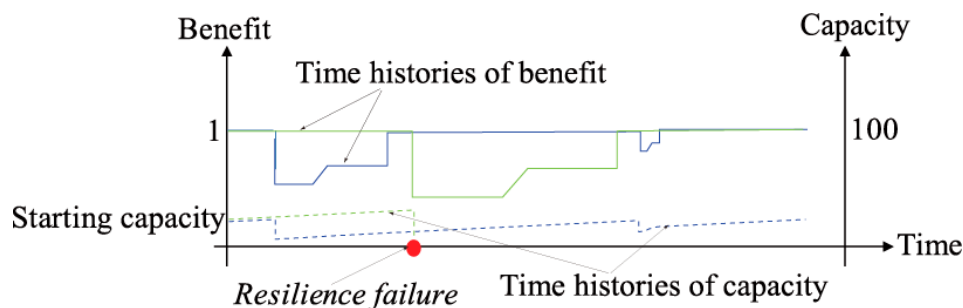

Figure 2. Illustration of the resilience model proposed in previous work [29], in terms of time histories of benefits and corresponding accumulated economic capacities (adapted from previous work [29]).

The event of resilience failure at time t may be defined in accordance with previous work [29] by the following limit state function:

$$g_{\text{RF}}(\mathbf{X}(t), \mathbf{a}) = r_r(\mathbf{X}(t), \mathbf{a}) - s_r(\mathbf{X}(t), \mathbf{a}) \tag{2}$$

where r_r and s_r are functions representing the capacity and the demand of the system at time t, respectively. The demand represents the effect on the system of any disturbance events that have the potential to reduce the capacity of the system. It should be noted that contrary to the focus of most research on systems resilience, not only are sudden and large consequence events are of relevance, but also effects of steady and low consequence events, such as degradation and lack of efficiency in integrity management, may be critically important.

The probability of occurrence of an event of resilience failure within the time interval $\Delta t_i = t_i - t_{i-1}$ (i.e., one year between year $i-1$ and year i) $P_{RF}(\Delta t_i)$ may be written as:

$$P_{RF}(\Delta t_i) = \int_{t_{i-1}}^{t_i} f^1(\tau) d\tau \tag{3}$$

where the first passage density $f^1(\tau)$ is determined from:

$$f^1(\tau) = \lim_{\Delta\tau \to 0} \frac{\Pr\left(\{g_{RF}(\mathbf{X}(\tau+\Delta\tau),\mathbf{a})\leq 0\}\cap\{g_{RF}(\mathbf{X}(\tau),\mathbf{a})> 0\}\right)}{\Delta\tau} \quad \forall \tau \subseteq [t_{i-1},t_i[\tag{4}$$

Generally, the solution to Equation (4) is not readily available, however, as indicated in the foregoing, the Monte Carlo simulation may be adequately applied.

4. Resilience Informed Decision Making Framework

Resilience modeling, as highlighted in Section 3, facilitates service-life based systems integrity management by informing decision making with respect to three different aspects, namely: (1) identification of acceptable decisions (domains in the space of decision alternatives for which the considered system fulfill potentially given requirements to resilience performances); (2) identification of decision alternatives associated with a positive net benefit or even maximizing service-life benefit; and (3) Value of Information (VoI) analyses, identifying the feasibility and optimality of different strategies for collection of information and establishing new knowledge.

Acceptable decision alternatives may be identified by assessing the probability of resilience failure P_{RF} for all possible decision alternatives contained in the vector **a**, and comparing with the maximum acceptable annual probability of resilience failure P_{RF}^A:

$$\begin{array}{c} \text{Identify } \mathbf{a} \\ \text{subject to } P_{RF} \leq P_{RF}^A \end{array} \tag{5}$$

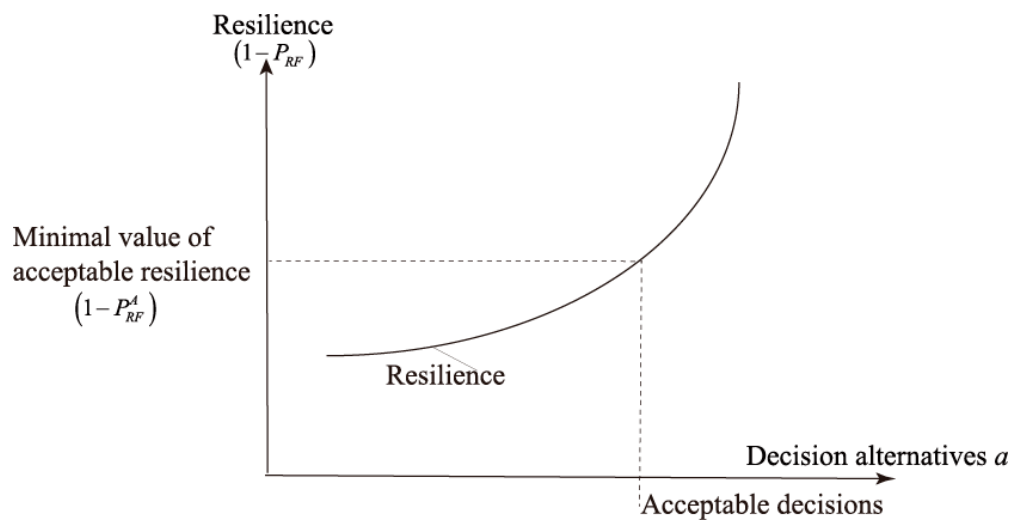Figure 3 illustrates the principle for the identification of acceptable decisions

Figure 3. Principal illustration of the identification of acceptable decisions.

Service life benefits are of central interest in the context of resilience management of infrastructure systems. In this context, however, it is important to note that there is a tradeoff between the expected value of a service life benefit and the probability of resilience failure. This tradeoff can be addressed in the context of ranking of decision alternatives in two principally different ways, namely: (1) by maximization of service life benefits under the constraint of a maximum acceptable annual probability of resilience failure; or (2) by maximization of service life benefits, including the risk of (expected value of consequences associated with) resilience failure. In the following, (1) is followed and it is assumed that a criteria is formulated which prescribes a maximum acceptable annual probability of resilience

failure P_{RF}^A. The optimization of service life benefits B_0^* may be then be written as (corresponding to a Bayesian prior decision analysis [36]):

$$B_0^* = \max_{\mathbf{a}}(E'_\mathbf{X}[b(\mathbf{X}(t), \mathbf{a})]) \\ \text{subject to } P_{RF} \leq P_{RF}^A \qquad (6)$$

where $E'_\mathbf{X}[b(\mathbf{X}(t), \mathbf{a})]$ represents the expected value of $b(\mathbf{X}(t), \mathbf{a})$ and the hyphen ' indicates that the probabilistic representation of $\mathbf{X}(t)$ is based solely on prior knowledge. The identification of B_0^* is illustrated in principal terms in Figure 4.
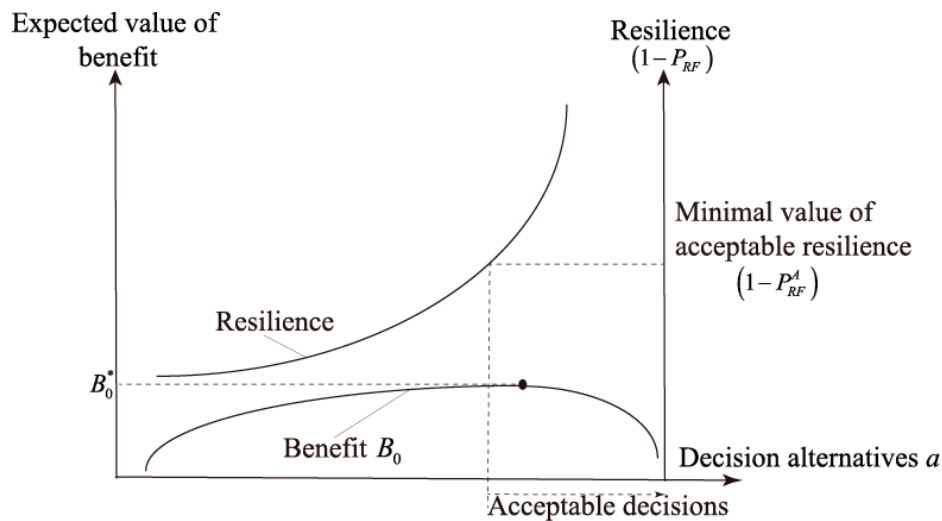

Figure 4. Principal illustration of the optimization of service life benefits B_0^*.

The concept of Value of Information (VoI) from the pre-posterior decision analysis has recently found extensive application in civil engineering applications [40–44]. Applied in the context of integrity management of infrastructures, VoI analyses commonly aim to identify potential savings in service life costs, or increases in service life benefits, related to different strategies for improving knowledge by means of collecting new information—through inspections, structural health monitoring, or by conducting laboratory experiments. Note that new information might not always have a positive impact on the service life benefits, if the system identification does not account appropriately for its source (see previous work [3] for further discussion). Extending on the decision optimization given in Equation (5), considering additional decision alternatives for collection of new information through an experiment e as a means of improving knowledge prior to choosing among the decision alternatives $\mathbf{a}$ (pre-posterior decision analysis). Then, the optimization problem may be stated as a normal form of pre-posterior decision analysis:

$$B_1^* = \max_{\mathbf{e}}(E'_\mathbf{Z}\Big[\max_{\mathbf{a}}(E'_\mathbf{X}[b(\mathbf{X}(t), \mathbf{a}, d(\mathbf{Z}))])\Big]) \\ \text{subject to } P_{RF} \leq P_{RF}^A \qquad (7)$$

where $\mathbf{Z}$ is a vector of random variables describing the uncertain realization of the new information and $d(\mathbf{Z})$ is a decision rule linking the new information to an explicit decision. The VoI associated with e may accordingly be determined as:

$$\text{VoI} = B_1^* - B_0^* \qquad (8)$$

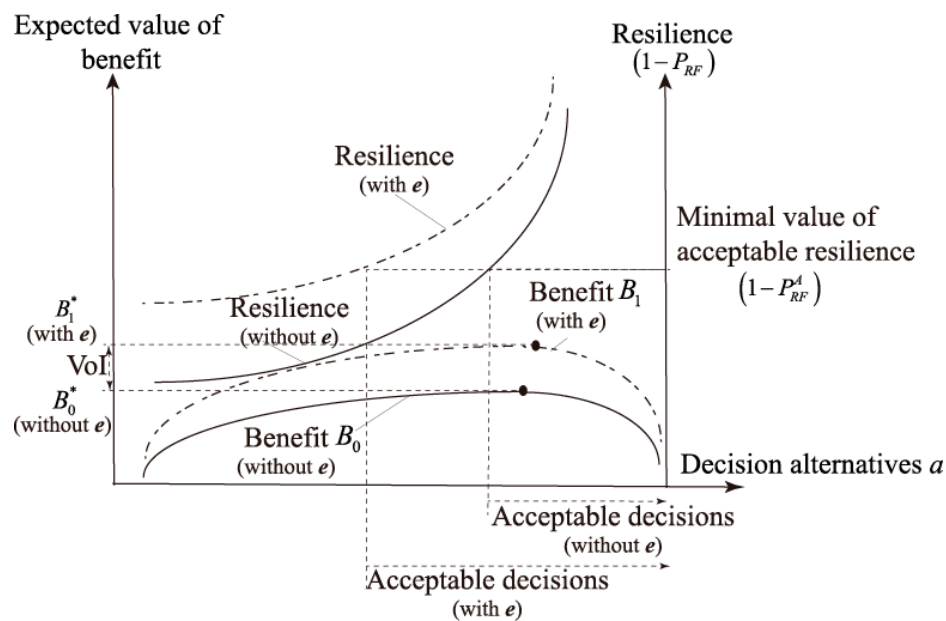The VoI analysis is illustrated in principal terms in Figure 5.

Figure 5. Principal illustration of the principle of VoI analysis for the optimization of service life benefits with given constraints on resilience performance.

5. Example

5.1. Introduction and System Definition

In the following, the resilience of an example wind turbine park is modelled and investigated as the basis for supporting decisions on service life asset integrity management. The decision alternatives considered include three different aspects of the management, namely: (1) the preparedness levels of the operator organization, reflecting the rapidity in dealing with the damages caused by possible disturbance events; (2) the target levels of design reliability for different sub-systems of wind turbines with respect to disturbances originating from extreme wind and normal operational load conditions; and (3) the percentage $\chi\%$ of benefits that is kept to build up economic capacity to deal with immediate losses (direct consequences) of disturbance events.

The example wind turbine park comprises 10 identical wind turbines of the type GE1.5 SLE, which all are assumed to be installed at the same time. The configuration and operational data for the considered type of wind turbines (GE1.5 SLE) may be found in previous work [45]. The service-life T of the wind turbine park is set to 30 years. For illustrational purpose, each wind turbine is composed of three different sub-systems, namely an electrical sub-system (such as generator and electrical control), a mechanical sub-system (such as mechanical brake and gearbox), and a structural sub-system (such as main shaft and rotor blade). The structural sub-systems are assumed to be exposed only to hazards originating from extreme wind events and the hazards to which the electrical and mechanical sub-systems are exposed are assumed to originate from conditions related to wear and other technical failures under normal operation. Concerning the failure rates of the mechanical and electrical sub-systems, it is assumed that these correspond to the constant values of typical representative bath-tub curves and may be defined in terms of the reciprocal of the mean time between failure (MTBF). Furthermore, the performance of each sub-system is described by Homogeneous Poisson Process (HPP) models [12,13]. That is, the long-term effect of the sub-systems' capacities, e.g., due to fatigue, is not considered here. Moreover, it is assumed that all wind turbines are subject, in principle, to the same demands and disturbances and are managed by the same owner or operator in accordance with the same management strategy.

The structural sub-systems across the wind turbine park are assumed to be exposed to natural hazards (extreme wind) with intensities L_H. The corresponding capacities of the structural sub-systems, r_H, are modelled by Log-normal distributed random variables, all with expected values and coefficients of variation equal to 1 and 0.3, respectively. The limit state functions representing the failure events of individual structural sub-systems with respect to natural hazards given in the form:

$$g_H = z_1 r_H - L_H \tag{9}$$

where z_1 is a parameter calibrated to comply with the target level of design reliability.

The occurrences of natural hazards events are assumed to follow a Poisson process with an annual rate $\lambda_H = 3$. The intensities of these events acting on each wind turbine within the park are modelled by a random vector of intensities $\mathbf{I}_H$, which are assumed to be Gumbel distributed. The intensities $\mathbf{I}_H$ acting on different wind turbines at a given time are assumed to be correlated with correlation coefficient $\rho_{\mathbf{I_H}}$. The expected values and the coefficients of variation of the components of $\mathbf{I}_H$, i.e., $E[\mathbf{I}_H]$ and $COV[\mathbf{I}_H]$, are set as equal to 1 and 0.4, respectively; and the correlation coefficient $\rho_{\mathbf{I_H}}$ is assumed as equal to 0.8.

To represent the random daily wind direction and the daily maximal wind for normal operation the wind scenario presented in a previous study [46] is utilized, as summarized in Table 1. The daily maximum wind speed v (at a given location, height, and direction) for all wind turbines across the wind turbine park is assumed to follow the same Weibull distribution. The wind direction is assumed not to influence the power generation but only the values of the parameters of Weibull distribution of wind speed, see Table 1.

Table 1. Operational wind scenario considered in the investigation (also see [46]).

Direction	Probability (Wind in this Direction)	Weibull Distribution Parameters		Direction	Probability (Wind in this Direction)	Weibull Distribution Parameters	
		k	c			k	c
0°~15°	0.0002	2	7	180°~195°	0.1839	2	10
15°~30°	0.008	2	5	195°~210°	0.1115	2	8.5
30°~45°	0.0227	2	5	210°~225°	0.0765	2	8.5
45°~60°	0.0242	2	5	225°~240°	0.008	2	6.5
60°~75°	0.0225	2	5	240°~255°	0.0051	2	4.6
75°~90°	0.0339	2	4	255°~270°	0.0019	2	2.6
90°~105°	0.0423	2	5	270°~285°	0.0012	2	8
105°~120°	0.029	2	6	285°~300°	0.001	2	5
120°~135°	0.0617	2	7	300°~315°	0.0017	2	6.4
135°~150°	0.0813	2	7	315°~330°	0.0031	2	5.2
150°~165°	0.0994	2	8	330°~345°	0.0097	2	4.5
165°~180°	0.1394	2	9.5	345°~360°	0.0317	2	3.9

k and c are the shape parameter and the scale parameter respectively.

The benefits gained from the individual wind turbines are realized through their power production. All of the wind turbines are of the same model and they have the same power generation function, which describes the relation between the power production and wind speed. Following the discussion in previous work [47–49], the power production P from each individual wind turbine, accounting for uncertainties, is modelled as:

$$P = \begin{cases} 0 & v \leq v_{in} \\ \frac{1}{2}\rho\pi R^2 C_p v^3 + \varepsilon & v_{in} < v \leq v_{rated} \\ P_{rated} & v_{rated} < v \leq v_{out} \\ 0 & v > v_{out} \end{cases} \tag{10}$$

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. P_{rated} is also referred to as the rated power, which is a characteristic for a given wind turbine model. ρ is the air density, R is the radius of the rotor, and C_p is referred to as the power performance coefficient, which varies with wind speed v. Finally, the variable ε represents a model uncertainty. The values of the radius of the rotor, the cut-in speed, the cut-out speed, the rated speed, and the rated power of the GE 1.5 SLE wind turbine are modelled as deterministic variables and taken from a previous report [45]. The air density ρ for the whole wind turbine park is set as equal to 1.00 kg/m^3, while the power performance coefficient C_p, which depends on the wind speed, is modelled in accordance with the onsite test presented in a previous report [45]. It is assumed that the model uncertainty ε follows a Normal distribution with expected value and standard deviation equal to 0 KW and 2 KW, respectively, as suggested in previous work [47]. For simplicity, it is further assumed that any two turbines in the park are separated sufficiently far from each other so that any interactions under operation are negligible.

5.2. Modeling of Failures, Event Scenarios and Consequences

Each sub-system is considered to have two potential condition states, namely, "survival" and "failure". Failure of any sub-system of one wind turbine is assumed to result in total loss of service from that turbine. The performances of the wind turbines may, thus, adequately be modelled through a series system, as illustrated in Figure 6, where also the demands and disturbances acting on the sub-systems are indicated. If one wind turbine performs well (no failure of any sub-system), it provides for its anticipated service, and generates electricity in accordance with design specifications. The benefit per unit time (year) provided by any individual 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., 1500 KW for the model GE 1.5 SLE. It is assumed that failed sub-systems are replaced immediately after failures with replacement costs, as specified in Table 2.
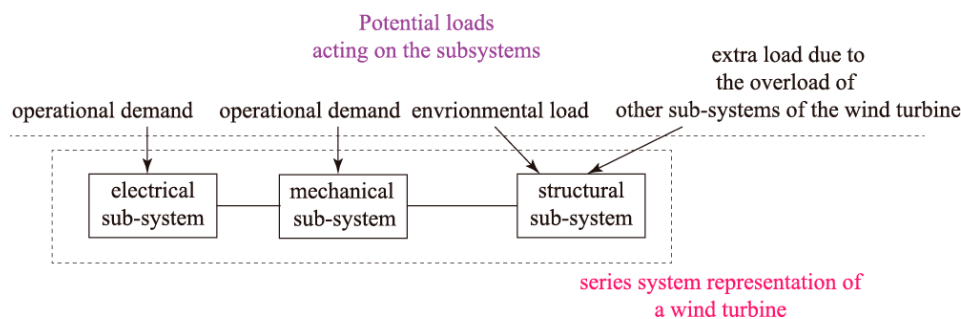

Figure 6. Illustration of the series system representation of the performance of a wind turbine.

Table 2. Replacement cost for different types of sub-systems.

Type of Sub-Systems	Replacement Cost
Electrical sub-system	0.3
Mechanical sub-system	0.2
Structural sub-system	1

The time history of the benefit generated from one wind turbine for a particular realization of a disturbance event is illustrated in Figure 7. At the time of the disturbance, the benefit generation is reduced to zero. Here, ΔT_1 represents the time interval from the time of the realization of the disturbance until the time at which the service of the wind turbine has been re-established. The time evolution of the benefit from the entire park is established as the simple sum of the benefits generated from the individual wind turbines. The period ΔT_1 describing the period of principal service loss and recovery curve is modelled by a Log-normal distributed random variable. The expected value $E[\cdot]$ and

the coefficient of variation $COV[\cdot]$ for ΔT_1 are assumed to depend on the chosen preparedness levels and the cause of the failure of the wind turbine. Two decision alternatives for the preparedness level, i.e., low and high, are considered. A high preparedness level implies a relatively small expected value of the recovery period and also a low coefficient of variation, while a choice of a low preparedness level is associated with the opposite effect. Replacement activities for the structural sub-systems are generally rather involved and time consuming in comparison to other sub-systems. Simultaneous failures of more than one sub-system are accounted for and the corresponding recovery periods are assumed equal to the recovery period of the sub-system with the longest recovery period. The probabilistic model for the recovery period ΔT_1 is defined in Table 3.
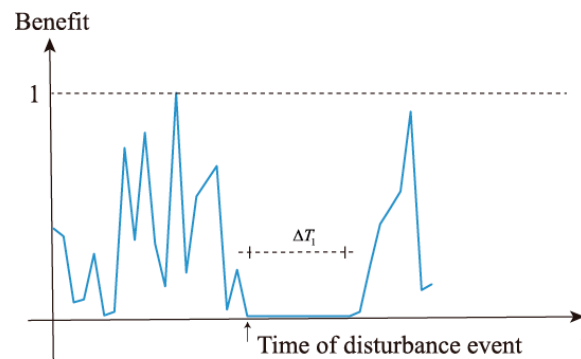

Figure 7. Illustration of the reorganization and recovery of the benefit of a wind turbine for one realization of a disturbance event.

Table 3. Definition of the probabilistic model of the recovery period ΔT_1 with respect to the type of sub-systems failure, as well as the preparedness level.

Distribution	Preparedness Level	Expected Value (Unit: month)			COV
		Structural Sub-System	Electrical Sub-System	Mechanical Sub-System	
Log-normal	Low	1	1/3	1/3	0.2
	High	1/3	1/9	1/9	0.1

5.3. Resilience Modeling and Resilience Failure Analysis

The resilience performances of the wind turbine park are now analyzed to assess how these may be managed optimally. The target design annual reliability for the sub-systems with respect to failures caused by disturbance events are calibrated through the values of z_1 and the MTBFs, respectively. Decision alternatives include wind turbines of two different levels of target design annual reliability. The corresponding values of the parameters relevant to the reliability of structural sub-systems and the reliability of the other two types of sub-systems are provided in Tables 4 and 5, respectively. It is assumed that failure of the electrical as well as the mechanical sub-systems of one wind turbine may induce additional loads of the structural sub-system of the same wind turbine, and thereby develop into cascading failure scenarios. The two groups of values of MTBF's defined in Table 5 are taken from previous work [12], in accordance with the results of statistical analysis of 10 years of operational data from wind turbines in Denmark and Germany, respectively. As outlined in the foregoing, it is assumed that the economic capacity of the wind turbine park is accumulated over the service life to facilitate for financing of required replacements of sub-systems upon disturbances. The start value of the economic capacity in the beginning of the service life is assumed as equal to a percentage $\chi\%$ of the expected value of the accumulated service life benefits.

Table 4. Parameters relevant to the design reliability of structural sub-systems with different target levels.

Target Level	Reliability Calibration		Conditional Failure Probability of the Structural Sub-System Given the Failure of the Electrical or the Mechanical Sub-System of the Same Wind Turbine
	Probability of Failure $\Pr(g_H<0)$	z_1	
Low	1.2×10^{-2}	2.5	0.3
High	1.1×10^{-3}	3.5	0.1

Table 5. Values of MTBF of electrical and mechanical sub-systems with different target levels of design reliability (unit is hours).

Target Level	Electrical Sub-System	Mechanical Sub-System
Low	25,708	90,472
High	450,643	1,236,712

Monte Carlo simulations are applied to assess the annual probability of resilience failure P_{RF} for different percentages $\chi\%$ and for four different scenarios, i.e., the combination of two different target levels of design reliability with two different levels of preparedness. The expected value of the total service life benefits of the wind turbine park is illustrated in Figure 8. It is seen that the expected value of service life benefits increases with the level of the chosen target design annual reliability and with the preparedness level. For the case of a high target level of design annual reliability, the expected value of total service life benefits is high, and correspondingly the influence of preparedness level is insignificant, due to the low occurrence probability of recovery activities. Furthermore, the annual probability of resilience failure for the case where a low target level of design annual reliability is selected is calculated for different values of $\chi\%$.; the results are illustrated in Figure 9, with each based on 1×10^4 Monte Carlo simulations. It is seen that the logarithm of the probability of resilience failure decreases for increasing values of the percentage $\chi\%$. As the percentage $\chi\%$ increases, the difference between the annual probabilities of resilience failure are more pronounced. For the case of a high value of the design target annual reliability, the annual probability of resilience failure is only notable when $\chi\%$ is 5% (in which case the annual probability of resilience failure is between 1×10^{-3} and 1×10^{-2}). This case is not shown in Figure 9.
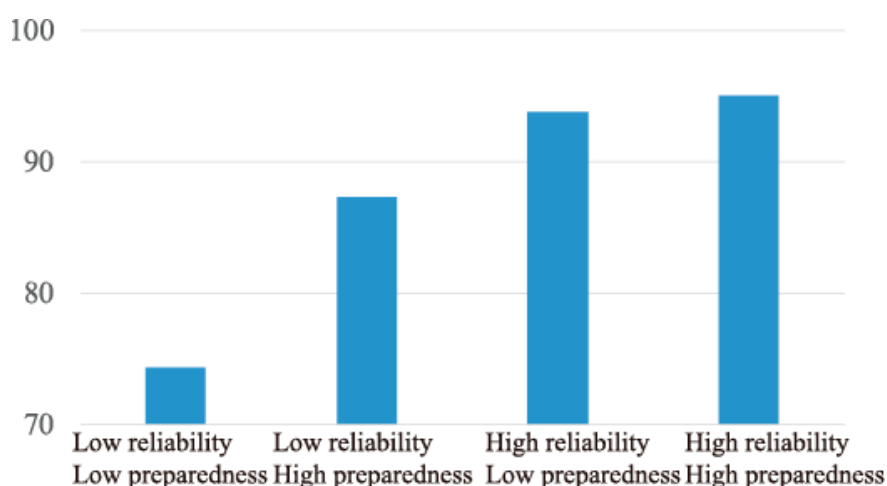

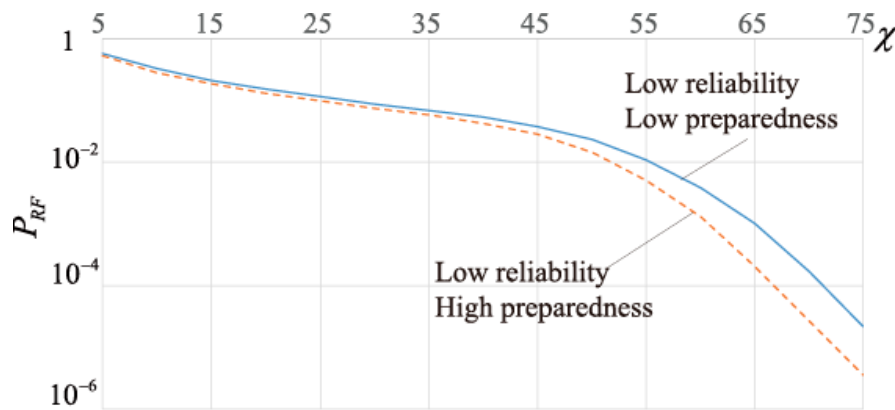**Figure 8.** Expected value of the total service life benefits.

Figure 9. Annual probability of resilience failure as a function of the percentage χ%.

5.4. Value of Information Analysis

To assess the potential benefit of using monitoring as a means for resilience informed integrity management, it is assumed that it is possible to collect new and perfect information relating to the performance of the individual sub-systems of the wind turbines through monitoring. Based on the monitoring results, it is further assumed that future failure events may be detected before they take place and that corrective actions may be implemented. As a result of early detection it is assumed that events of cascading failure can be avoided with certainty and that the replacement period can be substantially shortened, i.e., faster recovery and less interruption of production. In the context of VoI analysis, this case is often referred to as the case of "value of perfect information". For the purpose of illustration, the expected value of the recovery period given in Table 3 is assumed to be reduced by a factor of two as a result of early detection.

In Figure 10, the expected values of benefit generated by the wind turbine park with and without health monitoring are shown. For the case where a low target design level of the annual reliability of the wind turbine sub-systems is chosen, health monitoring increases the expected value of total benefit significantly. However, the difference is insignificant in the case where a high target level of design annual reliability is chosen, implying that for this case the benefit of health monitoring is insignificant. Further, for the cases of monitoring and no monitoring, given a choice of a low target level of design annual reliability, the annual probabilities of resilience failures are shown in Figure 11. It is noted that the annual probability of resilience failure in this case tends to decrease with increasing χ%. Moreover, it appears that monitoring reduces the annual probability of resilience failure significantly, both for the cases with high and low preparedness levels. Given that monitoring is implemented, it is also observed that the difference between the cases with high and low preparedness levels is negligible. For the cases with a high target level of annual reliability, the results are not shown in Figure 11. In these cases, resilience failures are only detected during the Monte Carlo simulations for very low values of χ% (5%), for which the annual probabilities are in the order of 1×10^{-3}.

The maximum achievable benefit from monitoring (since perfect information is assumed) may be assessed through the difference between the expected values of benefits taken at the χ% values, which exactly correspond to a given target annual probability of resilience failure, given monitoring and no monitoring, respectively. Thus, following the scheme introduced in Section 4, if the target annual probability of resilience failure is selected as 1×10^{-3}, the VoI, under the assumption of perfect information, which may be achieved from monitoring and given a low target level of design annual reliability, is found to reach around 30% of the total service life benefit.
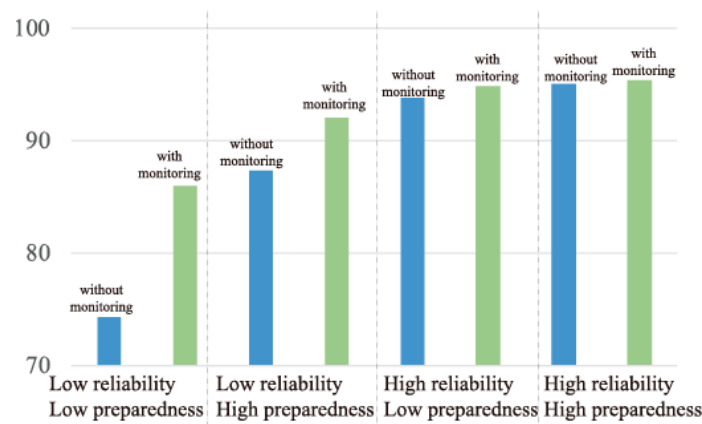
Figure 10. Comparison of the expected value of the total service life benefit of the wind turbine park with or without health monitoring.
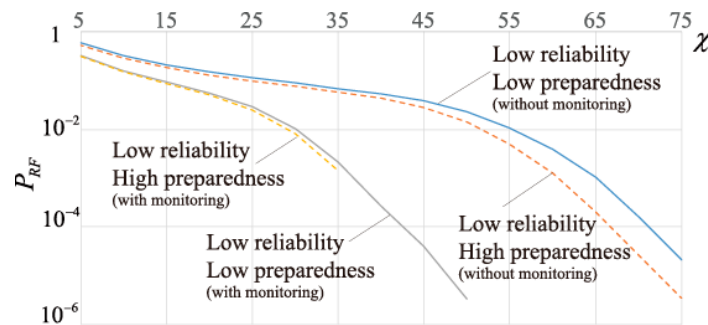

Figure 11. Comparison of annual probability of resilience failure as functions of the percentage $\chi\%$ for the wind turbine park with and without monitoring.

5.5. Down-Time Analysis and Spare Parts Stock Assessments

Based on the proposed resilience modeling framework, the reliability of the production down-time may readily be assessed. In order to illustrate this, the expected value of down time during the service life and the probability distribution of the number of simultaneous failures of the different types of sub-systems are investigated for each of the considered four scenarios. The results in terms of the expected value of power production down time (using 1×10^4 Monte Carlo simulations) are illustrated in Figure 12. It is seen that both the increase of target level of design reliability and the increase of preparedness level lead to reductions of production losses (in terms of expected value of down time). It is also seen that the effect on improved production from increased target levels of design reliability is rater dominant compared with the case of increased preparedness level.

As a result from the resilience modeling framework, optimal stock keeping of essential spare parts (sub-systems) may be assessed through the complimentary cumulative distribution of the number of simultaneous failures of different types of sub-systems (see Figure 13). Only up to 10 simultaneous failures of sub-systems are considered, since the probabilities of more simultaneous failures are diminishing. This observation is, however, specific for the present example, and the number of relevant simultaneous failures must be assessed from case to case.
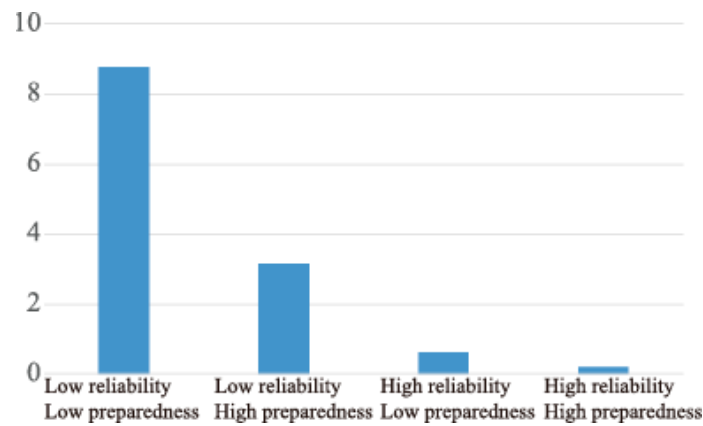
Figure 12. Expected value of production down time (number of wind turbines × year) over the service life of the wind turbine park.
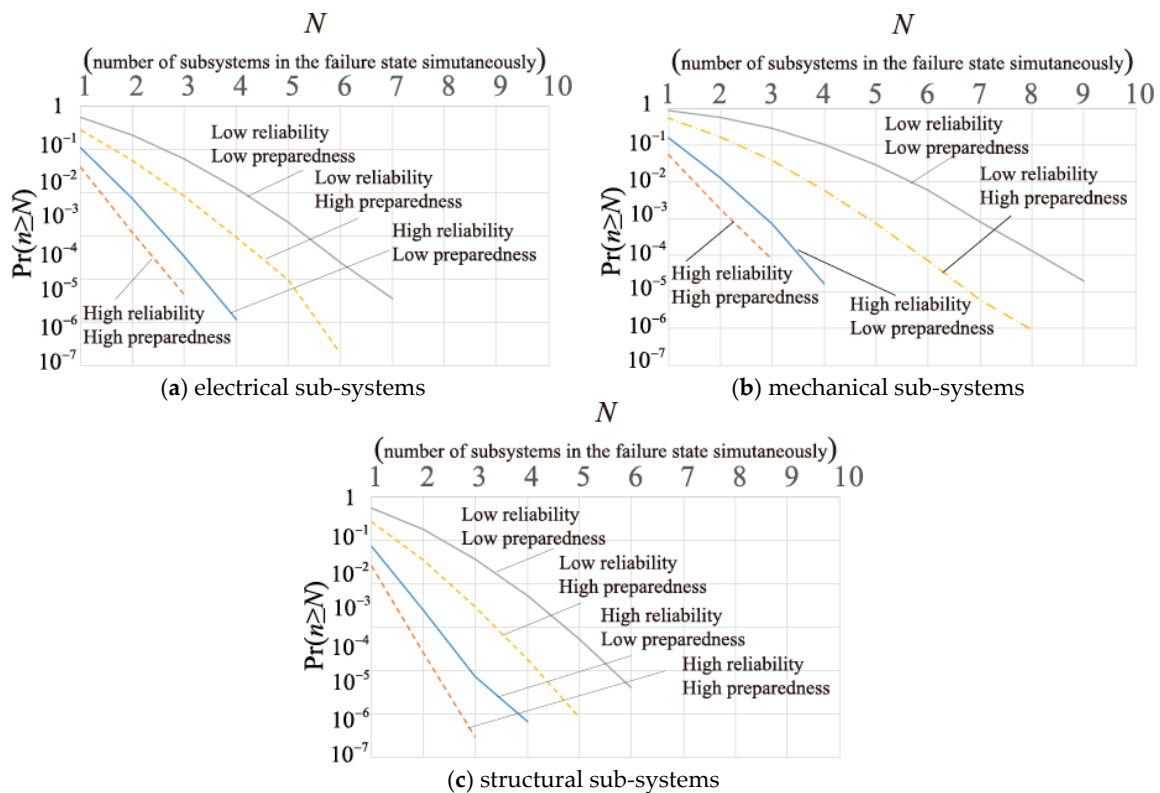

(**a**) electrical sub-systems

(**b**) mechanical sub-systems

(**c**) structural sub-systems

Figure 13. Complimentary cumulative distribution of number of simultaneous failures of different types of sub-systems.

6. Discussion

Resilience of systems as a concept originates from the natural sciences as a means for understanding and representing performance characteristics of ecological and socio-ecological systems under stresses from external disturbances. In engineering, the concept of resilience has gained significant interest in recent decades but has so far predominantly been applied in the context of supporting decision making at the societal community level, on how best to prepare for and react to natural hazard events, such as earthquakes and floods. The major benefit associated with the concept of resilience as compared to traditional probabilistic reliability and risk modeling of systems is that resilience modeling accounts for the interrelations between the performances of the natural systems and the social systems and their internal organization. Considering socio-ecological-technical systems, such as industrial production

systems, very little research, development, and application on resilience modeling is reported in the literature at the present stage.

In the present paper, a general framework for resilience modeling of systems developed previously by the authors is adapted to form a novel framework for resilience informed optimal decision making for integrity management of wind turbine parks. The framework facilitates a joint optimization of decisions on the design, operation, monitoring, and management of wind turbine parks from a service life perspective. The formulations proposed in the present contribution are directed toward the application for wind turbine parks but may easily be adapted to other types of industrial systems.

The general idea of the application of the framework is illustrated through an example considering a wind turbine park comprising ten wind turbines. The effects of uncertainties associated with the performances of the individual wind turbines and their sub-systems, the different levels of dependencies between the wind turbine park systems and sub-systems, as well as the failures or damages of different types of sub-systems are represented in the modeling and assessments through their effect on the time evolution of the benefits generated by the power production.

From the example, it is demonstrated that decisions on the target level of design annual reliability of individual wind turbines, the percentage of generated benefits that should be kept to ensure sufficient economic capacity to deal with future disturbances, and the organizational preparedness level may be optimized with given requirements to maximum annual probabilities of resilience failure. Moreover, it is illustrated how the concept of Value of Information analysis (VoI) facilitates the quantification of potential benefits of monitoring as a means to increase service life benefits from power production. Based on the proposed resilience modeling framework, the relevant performance indicators of the wind turbine park, such as the expected value of down time and the adequate stock keeping of essential spare parts, are readily quantified within the framework.

The resilience modelling presented in the present contribution is general, however, for illustrational purposes, the system representation of wind turbine parks is still rather simplistic. Future research on resilience management of wind turbine parks should extend and refine the modeling of deterioration (e.g., fatigue and corrosion) and strategies for inspections and maintenance. Further research could also provide new insights on the interrelations between choices among different operations and maintenance regimes and expected production performances. Finally, it should be noted that the developed framework also facilitates for gaining knowledge on the dependencies and trade-offs between requirements to resilience and risk financing, and thereby might inform decision making on the developments of the free market of renewable energies.

Author Contributions: The theoretical framework of resilience modeling and analysis was proposed by M.H.F. Author J.Q. developed the example and performed the investigations.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. WindEurope; Swiss Re. *The Value of Hedging— New Approaches to Managing Wind Energy Resource Risk*; Wind Europe: Brussels, Belgium, November 2017.
2. Afanasyeva, S.; Saari, J.; Kalkofen, M.; Partanen, J.; Pyrhönen, O. Technical, economic and uncertainty modelling of a wind farm project. *Energy Convers. Manag.* **2016**, *107*, 22–33. [CrossRef]
3. Nielsen, L.; Glavind, S.T.; Qin, J.; Faber, M.H. Faith and fakes—Dealing with critical information in decision analysis. *Civ. Eng. Environ. Syst.* **2019**, *36*, 32–54. [CrossRef]
4. Kozine, I.; Christensen, P.; Winther-Jensen, M. *Failure Database and Tools for Wind Turbine Availability and Reliability Analyses. The Application of Reliability Data for Selected Wind Turbines*; Technical University of Denmark: Lynby, Denmark, 2000; p. 47. ISBN 87-550-2732-6.

5. Sheng, S. *Report on Wind Turbine Sub-System Reliability—A Survey of Various Databases*; National Renewable Energy Laboratory: Golden, CO, USA, 2013; p. 43.

6. Branner, K.; Ghadirian, A. *Database About Blade Faults*; DTU Wind Energy E-0067; Department of Wind Energy, Technical University of Denmark: Roskilde, Denmark, 2014; p. 16.

7. Pedersen, T.F.; Wagner, R.; Demurtas, G. *Wind Turbine Performance Measurements by Means of Dynamic Data Analysis*; DTU Wind Energy: Roskilde, Denmark, 2016; p. 91.

8. Arabian-Hoseynabadi, H.; Oraee, H.; Tavner, P.J. Failure Modes and Effects Analysis (FMEA) for wind turbines. *Int. J. Electr. Power Energy Syst.* **2010**, *32*, 817–824. [CrossRef]

9. Chou, J.S.; Tu, W.T. Failure analysis and risk management of a collapsed large wind turbine tower. *Eng. Fail. Anal.* **2011**, *18*, 295–313. [CrossRef]

10. Shafiee, M.; Dinmohammadi, F. An FMEA-based risk assessment approach for wind turbine systems: A comparative study of onshore and offshore. *Energies* **2014**, *7*, 619–642. [CrossRef]

11. Reder, M.D.; Gonzalez, E.; Melero, J.J. Wind Turbine Failures—Tackling current problems in failure data analysis. *J. Phys. Conf. Ser.* **2016**, *753*, 072027. [CrossRef]

12. Tavner, P.J.; Xiang, J.; Spinato, F. Reliability analysis for wind turbines. *Wind Energy* **2007**, *10*, 1–18. [CrossRef]

13. Sørensen, J.D.; Toft, H.S. Probabilistic design of wind turbines. *Energies* **2010**, *3*, 241–257. [CrossRef]

14. Arwade, S.R.; Lackner, M.A.; Grigoriu, M.D. Probabilistic models for wind turbine and wind farm performance. *J. Sol. Energy Eng.* **2011**, *133*, 041006. [CrossRef]

15. Oyedepo, S.O.; Adaramola, M.S.; Paul, S.S. Analysis of wind speed data and wind energy potential in three selected locations in south-east Nigeria. *Int. J. Energy Environ. Eng.* **2012**, *3*, 7. [CrossRef]

16. Qin, J. Improved probabilistic modeling of wind speed in the context of structural risk assessment. *KSCE J. Civ. Eng.* **2018**, *22*, 896–902. [CrossRef]

17. Carta, J.A.; Ramírez, P.; Velázquez, S. A review of wind speed probability distributions used in wind energy analysis: Case studies in the Canary Islands. *Renew. Sustain. Energy Rev.* **2009**, *13*, 933–955. [CrossRef]

18. Tavner, P.; Edwards, C.; Brinkman, A.; Spinato, F. Influence of wind speed on wind turbine reliability. *Wind Eng.* **2006**, *30*, 55–72. [CrossRef]

19. Díaz, O.; Suárez, L.E. Seismic analysis of wind turbines. *Earthq. Spectra* **2014**, *30*, 743–765. [CrossRef]

20. Biehl, F.; Lehmann, E. Collisions of ships with offshore wind turbines: Calculation and risk evaluation. In *Offshore Wind Energy: Research on Environmental Impacts*; Köller, J., Köppel, J., Peters, W., Eds.; Springer: Berlin/Heidelberg, Germany, 2006; pp. 281–304. [CrossRef]

21. Hudecz, A.; Koss, H.; Hansen, M.O.L. Ice accretion on wind turbine blades. In Proceedings of the 15th International Workshop on Atmospheric Icing of Structures (IWAIS XV), St. John's, NL, Canada, 8–13 September 2013; pp. 1–8.

22. Byrne, B.; Houlsby, G.; Martin, C.; Fish, P. Suction caisson foundations for offshore wind turbines. *Wind Eng.* **2002**, *26*, 145–155. [CrossRef]

23. Faber, M.H. Resilient integrated energy infrastructures. In *DTU International Energy Report 2015*; Sønderberg Petersen, L., Ed.; Technical University of Denmark: Kongens Lyngby, Denmark, 2015; pp. 50–55.

24. Qin, J. Probablistic Analysis of Large-scale Engineered Systems. Ph.D. Thesis, ETH Zurich, Zurich, Switzerland, March 2012.

25. Derissen, S.; Quaas, M.F.; Baumgärtner, S. The relationship between resilience and sustainability of ecological-economic systems. *Ecol. Econ.* **2011**, *70*, 1121–1128. [CrossRef]

26. Linkov, I.; Bridges, T.; Creutzig, F.; Decker, J.; Fox-Lent, C.; Kroger, W.; Lambert, J.H.; Levermann, A.; Montreuil, B.; Nathwani, J.; et al. Changing the resilience paradigm. *Nat. Clim. Chang.* **2014**, *4*, 407–409. [CrossRef]

27. Qin, J.; Sansavini, G.; Faber, M.H. Probabilistic modelling of robustness and resilience of power grid systems. In Proceedings of the 2nd International Workshop on Modelling of Physical, Economic and Social Systems for Resilience Assessment, Ispra, Italy, 14–16 December 2017; pp. 23–35.

28. Faber, M.H.; Miraglia, S.; Qin, J.; Stewart, M.G. Bridging resilience and sustainability—Decision analysis for design and management of infrastructure systems. *Sustain. Resilient Infrastruct.* **2018**, 1–23. [CrossRef]

29. Faber, M.H.; Qin, J.; Miraglia, S.; Thöns, S. On the probabilistic characterization of robustness and resilience. *Procedia Eng.* **2017**, *198*, 1070–1083. [CrossRef]

30. Pimm, S.L. The complexity and stability of ecosystems. *Nature* **1984**, *307*, 321–326. [CrossRef]

31. Holling, C.S. Engineering resilience versus ecological resilience. In *Engineering Within Ecological Constraints*; Schulze, P., Ed.; The National Academies Press: Washington, DC, USA, 1996; pp. 31–43. [CrossRef]

32. Cutter Susan, L.; Burton Christopher, G.; Emrich Christopher, T. Disaster resilience indicators for benchmarking baseline conditions. *J. Homel. Secur. Emerg. Manag.* **2010**, *7*. [CrossRef]

33. Bruneau, M.; Chang, S.E.; Eguchi, R.T.; Lee, G.C.; O'Rourke, T.D.; Reinhorn, A.M.; Shinozuka, M.; Tierney, K.; Wallace, W.A.; Winterfeldt, D.V. A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthq. Spectra* **2003**, *19*, 733–752. [CrossRef]

34. National Research Council. *Disaster Resilience: A National Imperative*; The National Academies Press: Washington, DC, USA, 2012; p. 260. [CrossRef]

35. Qin, J.; Faber, M.H. Resilience informed performance assessment of infrastructure systems. In Proceedings of the 13th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP13), Seoul, Korea, 26–30 May 2019; pp. 2015–2022.

36. Raiffa, H.; Schlaifer, R. *Applied Statistical Decision Theory*; Harvard University: Boston, MA, USA, 1961; p. 380. [CrossRef]

37. JCSS. *Risk Assessment in Engineering—Principles, System Representation & Risk Criteria*; The Joint Committee on Structural Safety (JCSS): Zurich, Switzerland, 2008.

38. Faber, M.H. Risk and safety in engineering. In *Lecture Notes on Risk and Safety in Civil Engineering*; ETH Zurich: Zurich, Switzerland, 2009.

39. Marti-Puig, P.; Blanco, M.A.; Cárdenas, J.J.; Cusidó, J.; Solé-Casals, J. Feature selection algorithms for wind turbine failure prediction. *Energies* **2019**, *12*, 453. [CrossRef]

40. Pozzi, M.; Der Kiureghian, A. Assessing the value of information for long-term structural health monitoring. In Proceedings of the Health Monitoring of Structural and Biological Systems, San Diego, CA, USA, 18 April 2011.

41. Faber, M.H.; Thöns, S. On the value of structural health monitoring. In *Safety, Reliability and Risk Analysis*; CRC Press: Wroclaw, Poland, 2013.

42. Straub, D. Value of information analysis with structural reliability methods. *Struct. Saf.* **2014**, *49*, 75–85. [CrossRef]

43. Konakli, K.; Faber, M.H. Value of information analysis in structural safety. In *Vulnerability, Uncertainty, and Risk: Quantification, Mitigation, and Management*; Beer, M., Au, S.K., Hall, J.W., Eds.; ASCE: Liverpool, UK, 2014; pp. 1605–1614.

44. Qin, J.; Thöns, S.; Faber, M.H. On the value of SHM in the context of service life integrity management. In Proceedings of the 12th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP12, Vancouver, BC, Canada, 12–15 July 2015.

45. Mendoza, I.; Hur, J.; Thao, S.; Curtis, A. *Power Performance Test. Report for the U.S. Department of Energy 1.5-Megawatt Wind Turbine*; National Renewable Energy Laboratory (NREL): Golden, CO, USA, 2015; p. 52.

46. Kusiak, A.; Song, Z. Design of wind farm layout for maximum wind energy capture. *Renew. Energy* **2010**, *35*, 685–694. [CrossRef]

47. Jin, T.; Tian, Z. Uncertainty analysis for wind energy production with dynamic power curves. In Proceedings of the 2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems, Singapore, 14–17 June 2010; pp. 745–750.

48. Mendoza, I.; Hur, J. *Power Performance Test. Report for the SWIFT Wind Turbine*; National Renewable Energy Laboratory (NREL): Golden, CO, USA, 2012; p. 48.

49. Carrillo, C.; Obando Montaño, A.F.; Cidrás, J.; Díaz-Dorado, E. Review of power curve modelling for wind turbines. *Renew. Sustain. Energy Rev.* **2013**, *21*, 572–581. [CrossRef]