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Chapter 12

Towards smart, efficient and reliable wind-turbine structures

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DTU Wind Energy

A sustainable world requires better structures

In this chapter, we describe our vision for creating better and safer wind turbine structures. Our aim is to outline a pathway leading to continuous improvements in their structural design and operation. In order to facilitate the discussion, let us first define what we mean by better structures. Comparing designs among the same family of structures, a specific structural design can be considered *better* if the costs of manufacturing, installation, operation, maintenance and decommissioning is low and/or if its level of performance, reliability and safety is high. In recent years, the sustainability of such structures and mitigating their environmental impact have been gaining significant attention. Better designed structures should therefore have little if any negative impact on the environment. For example, low-carbon footprints can be achieved by incorporating clear considerations of post-service life in terms of the reuse of structural components and recyclability into future design processes.

The goals of creating better wind turbine structures, are ambitious, but they are becoming more and more achievable through a combination of several development leaps in key enabling technologies:

- digitalization such as big data and the internet of things to facilitate information flows in operational wind turbine structures.
- artificial intelligence such as machine-learning to analyse information and support decision-making with, for example, predictive inspection and maintenance schedules.
- advanced sensors, which are expected to become cheaper, smaller, smarter, wireless and self-powered, providing a comprehensive sensing network for wind turbine structures.
- autonomous drone and robotic systems that can carry out damage inspections and make the necessary repairs efficiently.
- novel manufacturing methods such as 3D printing that can produce structures and components with complex shapes and optimised material properties beyond the feasibility of current manual manufacturing methods.

This list emphasises not only the demand for the further development of each individual field, it also shows the necessity of integrating these key enabling technologies into one unifying framework through collaborative, interdisciplinary effort.

Designing better wind turbine structures requires using materials closer to their limits, which in turn necessitates advances in the trinity of key fields in structural design: material science, manufacturing methods, and numerical simulation and experimental capabilities. We rely on material science to discover new material systems and to improve existing ones, for example, developing novel resin systems for fibre composites with increased damage tolerance and higher fatigue strength or steels that are more resistant to wear, corrosion and fatigue. However, the development of these new materials alone is not sufficient, as it is just as important to improve existing manufacturing methods, as well as create the radically new manufacturing methods that will be needed in order to produce structures incorporating these materials consistently with the desired properties and geometrical shapes. Novel manufacturing methods such as the 3D printing of continuous fibre composites will enable the production of material fibre architectures whose realization is not feasible using current technologies (e.g. glass fibre fabric vacuum infusion). New manufacturing methods have the potential to increase the reliability of structures and materials significantly due to their improved consistency in production and – equally important – due to tailoring material properties to the specific purpose and operating conditions.

In order to utilise both materials and manufacturing capabilities fully, the design of better structures relies heavily on the development of multi-scale numerical prediction capabilities. The ongoing challenge is the development of numerical modelling strategies that can efficiently model damage and fracture processes with a characteristic length scale of micrometres in large-scale structures with a characteristic length scale of hundred metres. In recent decades, research in this field has mainly focussed on improving the accuracy and fidelity of the numerical models. However, the development of computationally efficient models has gained considerably in importance in order to make them compatible with machine-learning technology in general and with digital-twin technology in particular. It is therefore no longer sufficient to make accurate predictions alone, as these predictions should also

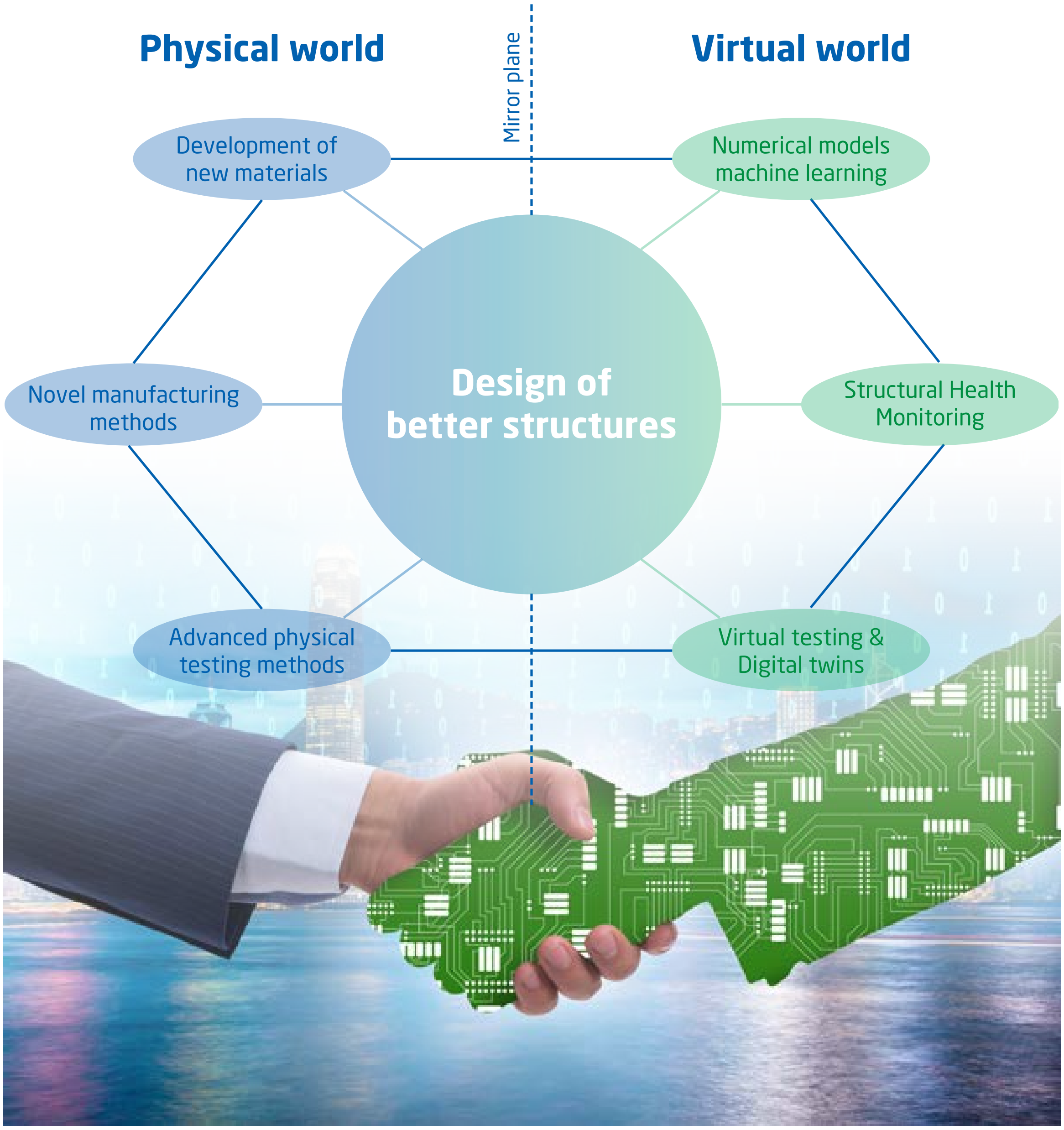

Figure 1.
Illustration of the trinity of structural design key fields: material science, manufacturing methods, and numerical/experimental methods, mirrored with the trinity of Structural Health Monitoring (SHM): measurements, evaluation and numerical/operational methods.

be optimized in terms of both accuracy and speed. In a sense, the developers of numerical prediction tools find themselves faced with the need to break the sound barrier of computational speed. That is to say, machine-learning relies on the ability to solve a comprehensive set of numerical simulations of the evolution of damage and fracture in large structures efficiently in order to train the algorithm. In addition, probabilistic design frameworks require the computation of a vast number of different simulations, placing a considerable burden on model running times. For example, in the case of simulations of fatigue damage, current running times for large-scale models that take days need to be reduced to the running times of minutes that approximate to quasi-real-time prediction capabilities.

However, designing better structures closer to their limit by using better materials, manufacturing methods and numerical/experimental methods is only one side of future design philosophies (see Figure 1). In current design philosophies, the degree of structural utilization is defined at the drawing board, and costly reactive maintenance schemes are employed to maintain consistent structural integrity. The design philosophy of tomorrow's wind turbine structures will see a paradigm shift as structures will become smart through their ability to communicate their structural health status and predictively adapt their mode of operation individually according to their structural health status.

Like a human being's medical records, a structural health journal will be maintained for every individual structure to record the history of every incident, which will be uniquely mapped for each damage event present in each component of the structure. Structural-health monitoring systems will be able to track the evolution of existing damage and identify the appearance of new induced or inflicted damage. The information in the structural health journal will be stored in the structure's digital twin, which is synchronised and updated with a live feed from the structural-health monitoring system. Making computationally superefficient numerical material and structural models part of the digital twin will enable the individual admissible structural utilisation level to be assessed based on the prevailing damage state. In this way, the structural utilization can be adjusted individually and predictively for every wind turbine structure to ensure its maximum structural life.

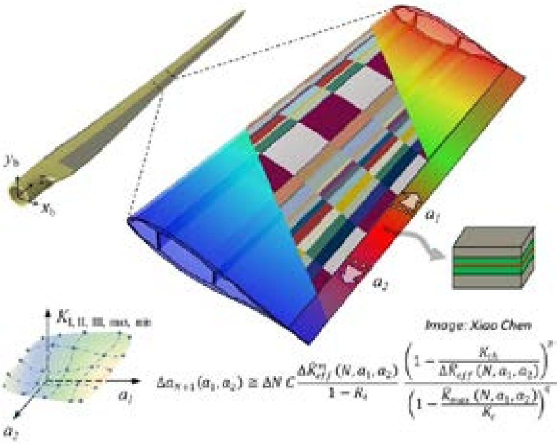

Figure 2.
The developed FASTIGUE approach based on fracture mechanics resolves the heavy computational demands of fatigue crack simulation for large structures such as composite wind turbine blades, thus providing super-fast computational capability to enable a digital twin in near real time [1].

Impact of industry trends on structures

The size of wind turbines is still increasing, and there is no sign that this process will end any time soon. This requires the testing of ever larger components, which in turn requires ever larger test facilities, test stands and test-loading equipment which must soon be capable of accommodating +15 MW turbine components. Blades are tested at their resonance frequency, as brute force testing requires too much force and energy, making it unfeasible. The resonance frequency decreases with increasing blade size, meaning that the time required for the test becomes longer. For comparison, the certification test time of modern large utility +100 m blades can exceed one year, which emphasizes the need to shorten the time to market. Thus, the testing of individual components is becoming extremely costly and time-consuming to perform. One way to overcome this would be to divide very large components into more manageable sections and have them tested separately while simulating the full-scale or full-system test. Such tests require new research and the development of new testing methods, as well as computer models to simulate full-scale testing. While performing component tests section-wise with full-scale test simulations may be less expensive and faster, there will still be a need to be demonstrate the methodology in full-scale tests at realistic loadings. One result of the project BLATIGUE [2] is the development of an optimized method for the multi-axial fatigue testing of wind turbine blades. Using this method, improved fatigue tests compared to current standard fatigue tests were obtained in terms of both accuracy and total test times [3]. In this approach, the response of the blade is calculated at the material level by considering strain-based damage targets. An optimal combination of different test blocks (i.e., flapwise, edgewise, chaotic and phase-locked) can be obtained to reach the damage targets in the entire blade while minimizing the total test time, thus satisfying predefined error limits.

Figure 3.
Steel plates with a vertical weld in the centre before immersion into the North Sea at the Fraunhofer Institute offshore corrosion test site on Heligoland. The steel plates were recovered from the water after seven months of exposure and cut into dog bone-shaped specimens to determine the effect on the fatigue life of the welds after corrosion. The work was performed within the WindWeld project [4].

Another critical component requiring improved test facilities is the blade bearings, which connect the blade root to the rotor hub. The continuing increase in the bladeroot diameter and in blade length and weight is resulting in higher loads being placed on these bearings. Blade bearings have to withstand high bending moments while standing still or rotating at very low speeds. Major bearing manufacturers and OEMs have in-house blade-bearing test rigs, but due to the prohibitive costs, there is a need for independent test providers. Current blade-bearing test facilities at Fraunhofer IWES in Hamburg and Windbox in Bilbao can perform tests of up to 8-10 MW turbines, but even this is insufficient for the new generation of turbines. There is an increasing need in the sector for access to a strong palette of independent test facilities and more accurate testing methods.

Given the increasing worldwide trend for wind turbines to move offshore, corrosion fatigue is becoming increasingly important for designing monopiles and floating support structures exposed to both wind and wave loads in the harsh offshore environment (see Figure 3). Corrosion fatigue refers to a situation in which the mechanically driven deterioration of a material due to cyclic loading is exacerbated by an electrochemical corrosion process. This results in a situation in which the fatigue life of a structure that operates in mild conditions can be significantly reduced when operating in corrosive conditions. The mechanisms involved in corrosion fatigue are complex and still poorly understood. Current offshore structures are often unique or manufactured in small quantities, designed from standards based on current best practices. These standards are conservative, incorporating considerable safety factors established by both the maritime and the oil and gas industries.

These high safety factors are applied because of the lack of knowledge about the magnitude of the influence of corrosion fatigue in different environments. High safety factors are therefore necessary to cover important effects conservatively, such as temperature and chemical seawater composition. However, this is only possible if the actual corrosion fatigue resistance of a structure can be fully utilized, and this requires comprehensive fatigue tests that are time-consuming and costly. Normal fatigue tests under ambient inert conditions can be accelerated, but this acceleration is rather difficult when dealing with corrosion fatigue. This bottleneck prevents the availability of sufficient corrosion fatigue test numbers, which presents challenges in obtaining statistical results from large-scale fatigue tests in relevant offshore environments, as illustrated in Figure 3. New, more realistic testing methods will be required to establish new corrosion fatigue design standards for offshore wind-energy structures, which is a challenge to the industry. These test developments pertain to standardized and hence comparable pre-corrosion procedures for test coupons and require access to X-ray computer tomography facilities that can scan representative areas of corroded samples with sufficient resolution. Moreover, fatigue test methods must also be developed than can handle corroded large-scale fatigue test coupons, as well as new in-situ corro-

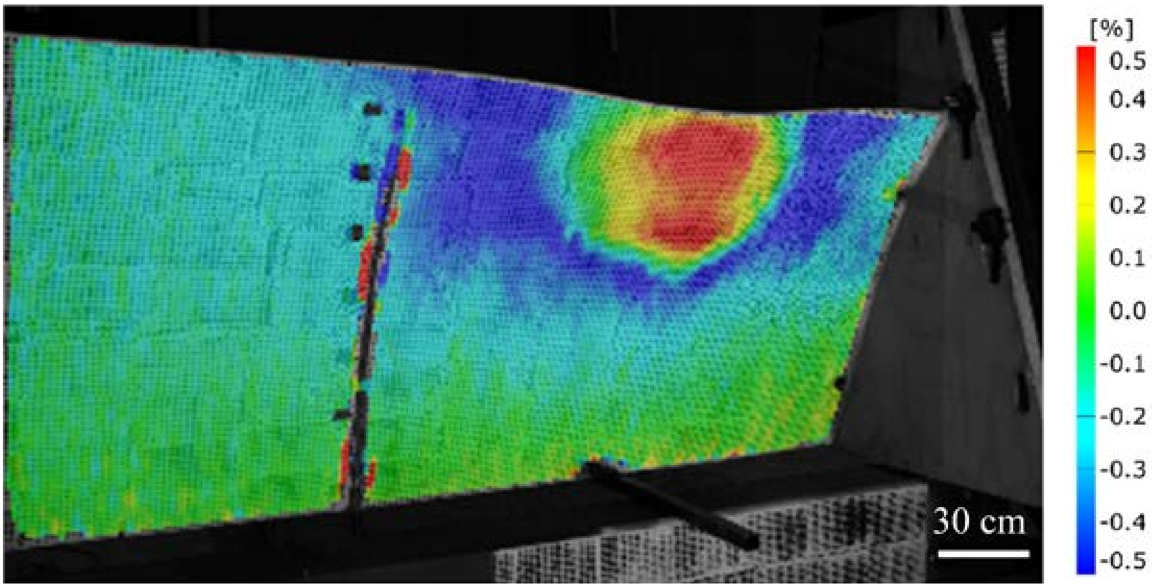

Figure 4.
The full-field longitudinal strain measurement of a trailing-edge subcomponent from a digital image correlation system shows that such complex buckling-driven failure processes can be only discovered using advanced testing and delicate measurement. This fosters an in-depth understanding of the new phenomena to further establish reliable numerical models for accurate predictions, thus providing a solid foundation for the development of key enabling technologies for smart, efficient and reliable wind-turbine structures [6].

sion fatigue test methods in which the specimen is fatigued inside a corrosive electrolyte.

Another trend is to utilize integrated system design and optimized design processes in order to decrease costs. Also, the trend towards industrialization and standardization will result in the mass production of wind turbine structures on a scale not seen before, which will reduce costs. Producing large amounts of components in larger quantities than has been done up to now is needed generally to meet the climate goals. Also, a direct calculations method to design wind turbine structures and predict how and when they will fail is increasingly in demand.

The value of testing structures

Virtual testing and virtual measurement are novel areas of increasing importance, forming a field that complements physical testing. Virtual testing in this context refers to a numerically simulated test with the aim of predicting the physical properties of a virtual specimen, as they would have been obtained in a physical test. The big potential of virtual testing is seen when it is combined with machine learning, as the optimal set of material parameters can be obtained without the necessity to conduct comprehensive and costly testing. Measurements using virtual sensors make it possible to 'measure' where it is not possible to place physical sensors. What can be observed is the clear trend that virtual testing and physical testing are moving closer together. In fact, a physical test must be treated as a model of reality quite as much a numerical model claims to be. The sophistication of both numerical and physical testing models is constantly increasing, and both can be considered to converge asymptotically.

Despite the celebrated advantages virtual testing has to offer, replacing physical testing entirely with virtual testing will not, in our view, be tenable. An analogy to replacing physical testing with virtual testing is exploring the world solely by means of Google maps. We believe that a true exploration of nature needs a connection between the virtual world and the physical world. Physical testing is essential in order to go deeper and expand our knowledge and understanding at all scales, i.e. microscale to macroscale; in our opinion this will remain an indispensable requirement for many decades to come. The promising developments in virtual testing will assume an important supplementary role for testing, but will complement rather than supersede physical tests.

The statement regarding the indispensability of physical tests deserves a more thorough corroboration: the physical processes inherent in structural behaviour present at different characteristic length scales are emergent [5]. Emergence in the context of material- and structural testing (see Figure 5) is defined as a physical property (e.g. nominal strength) of a specimen that cannot be observed in its individual constituents (e.g. atomic bond strength), but rather emerges through the interaction of many constituents in the bulk, depending on the scale of the testing. This means that a measured physical property such as fatigue strength will depend on the characteristic scale of testing, which consequently hinders the prediction

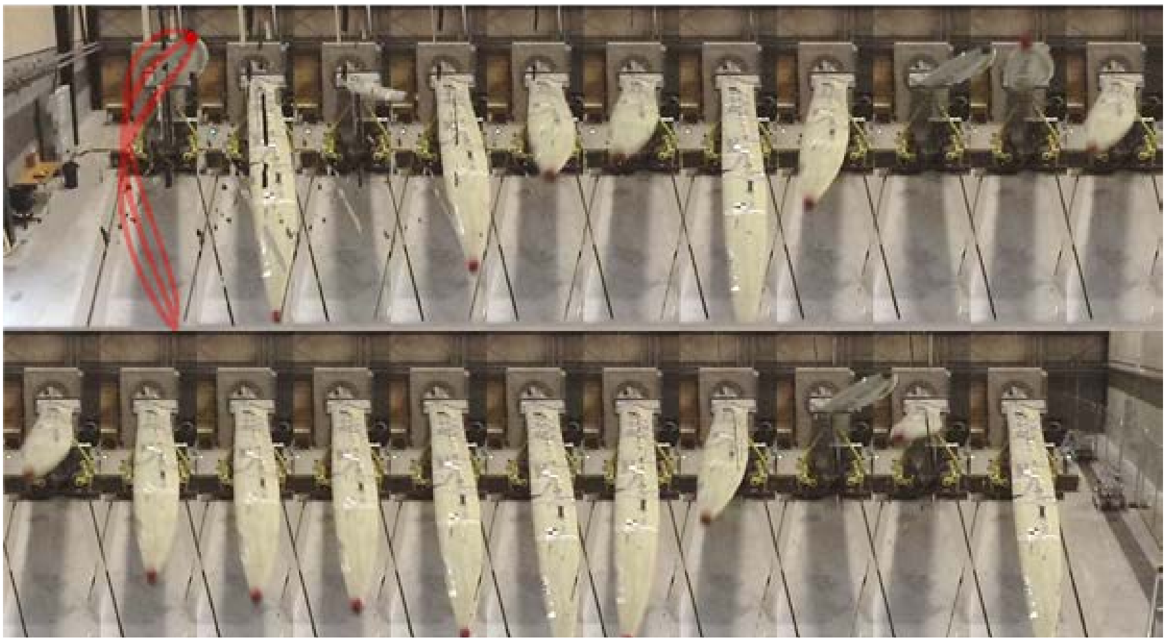

Figure 5.
A 14.3 m long blade under biaxial fatigue being excited by a ground-based dual-axis exciter developed within the BLATIGUE project (Fast and Efficient Fatigue Test of Large Wind Turbine Blades). A clown nose is mounted at the tip of the blade to help visualize its trajectory, whose one-second data is superposed in the figure and shows the response of the blade under biaxial cyclic loading [7].

of a physical property on the macro-scale based on observations made on the micro- or nano-scales. Such emergent behaviour is quite apparent in the evolution of fatigue damage in metals and fibre composites. In general, emergence counters reductionism, as the fatigue behaviour of a macro-scale structure cannot be predicted from first-order principles, such as laws describing the strength of molecular bonds in polymers or dislocation motion in metallic lattices on the micro-scale.

Emergence is the predominant source of the so-called 'size effect', which accounts for the fact that, for instance, the fatigue behaviour of the same material system can be vastly different at different scales. Existing approaches aimed at correcting for the size effect are based on statistical physics or damage/fracture mechanics and cannot themselves be derived from the first-order principles. In other words, emergence prevents the formulation of a single unifying theory that uses first-order principles to describe the fatigue behaviour of a material at all characteristic length scales. The lack of such a unifying theory means that any virtual testing simulation must be based on material models that are only valid at or are a good approximation to a specific length scale. From this, it can be inferred that any virtual testing simulation requires material input parameters that stem from a lower scale, which the virtual test itself cannot predict. These material input parameters have to be obtained from a physical test, emphasising the need to test materials, components and structures physically at all scales.

Therefore, the development of more sophisticated testing methods capable of simulating real-life operational conditions, especially on subcomponent scale (characteristic length 1m; see Figure 4) and full-scale (characteristic size 100 m), will increasingly become a focus of experimental research. There is a particular demand for research on fatigue-testing methods (i.e. testing under cyclic-loading conditions) with the ability to consider the complexity of realistic loading scenarios, as well as environmental operating conditions, e.g. in-situ corrosion fatigue, erosion, sub-zero conditions and humidity (see Figure 5).

The need for improved mechanical and physical testing is also driven by the demand to develop more computationally efficient numerical models through observation (e.g. in-situ measurements and post-mortem analyses) in order to incorporate specific phenomena that avoid computationally expensive methods. The FASTIGUE method [8] is an example of a computationally efficient method. Such methods are needed to predict the consequences of damage growth, which, for example, can be detected using thermography and computer vision, as shown in Figure 6 using the AQUADA method [9]. The development of more sophisticated subcomponent testing methods that can capture the effect of macroscale features and defects at full

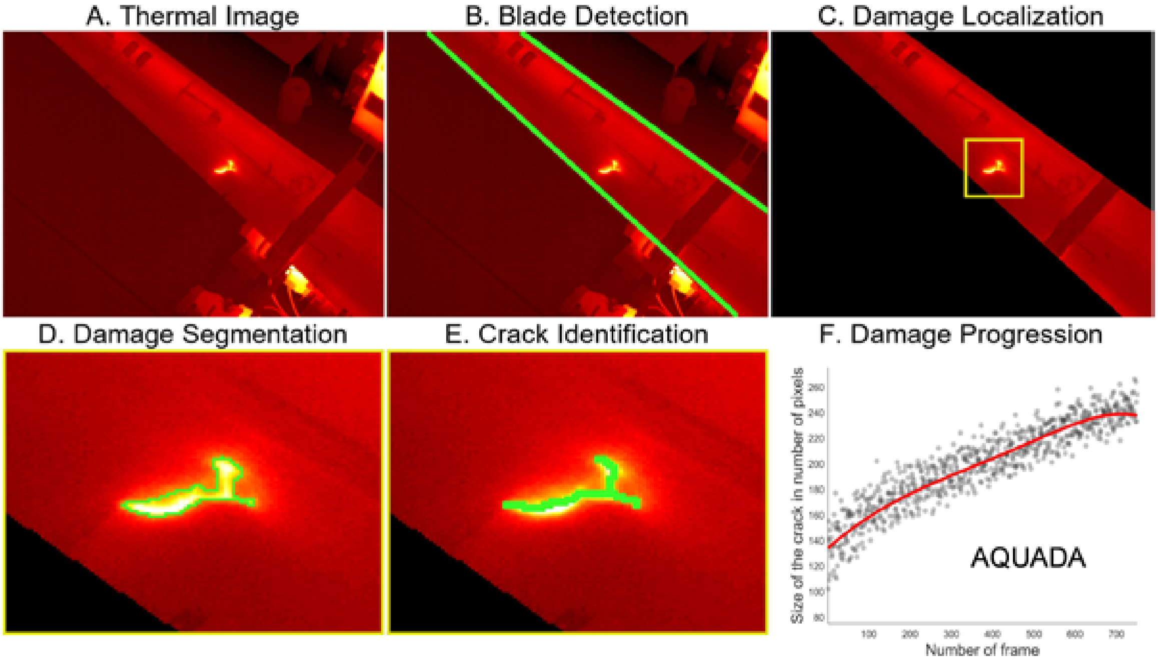

Figure 6.
Using thermography and computer vision, in its large-scale facility, DTU Wind Energy has demonstrated that the developed AQUADA method can monitor and quantify the progress of fatigue damage in a full-scale blade in near real time. The figure shows a progressive crack close to the trailing edge that has been identified, tracked and analysed to assess its damage criticality. The LCoE calculation shows a great potential to reduce the O&M cost of the wind-turbine blades if the AQUADA method were to be applied to a real wind farm in the field [9].

scale, such as adhesive bondlines in tapered beams, ply drops, wrinkles and welded connections, are an important means to calibrate numerical models on intermediate scale, necessary to predict the behaviour at full scale both accurately and efficiently (see Figure 4).

Linking the physical and virtual world via digital twins

The term '*digital twin*' has many different definitions used in both academia and industry in a rather broad sense. However, in this chapter we follow the definition of Bolton et al. [10], that a digital twin is a '*dynamic virtual representation of a physical object or system across its lifecycle, using real-time data to enable understanding, learning and reasoning*'.

According to our vision the digital twin of a wind turbine is connected to the real structure through a live feed of data streamed from embedded sensors, meteorology data and most importantly from structural health monitoring systems and inspection systems. Ideally, therefore, a digital twin can be used to make predictions of the development of damage, e.g. in the blade, based on the current damage state that is recorded and updated in a structural health journal maintained for each and every blade (or other structural components for that matter). Based on physical models, the digital twin can then be used to simulate the effect on the structure for different damage modes and different operational scenarios, e.g. in the event of a storm, grid loss, the shutting down of a wind farm. Despite these extreme load cases, the digital twin will also be used to predict the adverse effects of high turbulence levels and wake effects that might be caused by certain weather conditions or the effect of wind speed and particle size (droplets or ice crystals) on the blade erosion potential. The project RELIABLADE develops and demonstrates techniques to create a unique digital twin for each individual wind-turbine blade with their unique defects and imperfections. The aim is that the digital twin should track the current state and predict the future state of the blade as damage is caused and grows through its entire life-cycle [13].

However, the digital twin reveals its true future power through the deployment of a form of artificial intelligence (AI) that can operate individual wind turbines, an entire wind farm or even the whole energy system. The digital twin can solve a huge set of problems and scenarios that will be used to train the AI to make optimal decisions for individual turbines with an efficiency beyond any existing human operation and maintenance schemes. In other words, the digital twin makes simulations that help to establish the parameter space and its sensitivities. The AI will then be able to make decisions for operating individual turbines in fractions of a second, thus taking on the role of predictive maintenance. It will consider the structural health of each turbine when making decisions on how close to the limit it will drive or operate the turbine according to the objective function of the asset optimization. A flow diagram connecting the different elements of such a human-cyber physical system is shown in Fig. 7. The use of digital twins at the farm level is described in Chapter 11 and at the materials level in Chapter 13.

Condition monitoring and predictive maintenance

Corrective or reactive maintenance means that maintenance activities begin only after the failure of concern has already occurred. On the one hand, this means that all the maintenance effort becomes critical to correct the health and operational capacity of the structure; on the other hand, the risk of large or even catastrophic damage occurring in the wind turbine is increased. Preventative maintenance can give early warning of incipient damages if inspections are carried out regularly, but this means effort being expended on manual inspections of structures that require no maintenance, which is very expensive for offshore structures requiring trained and qualified technicians.

Reliability-based and risk-based inspection strategies represent a balance between the risks and rewards of corrective and preventative maintenance by integrating prognostics and crack-growth modelling, with the potential consequences of different failures and their inspection and repair costs. However, we believe that the real-time, remote condition monitoring of structural health will play a key role in the future to enable the unfolding of the digital twin technology outlined above and permit true condition-based maintenance where the integrity of the structure is permanently observed.

Structural health monitoring (SHM) must be able to (i) detect the presence of a defect or damage; (ii) classify the damage type; (iii) triangulate its precise location in the structure; (iv) measure the size and extent of the damage; and (v) be able to measure and track the growth of the damage reliably. The distribution of 'readiness levels' for SHM technologies on wind turbine blades is very broad. For many years, rope-access technicians (RATs) provided the only information about structural health status to owners and operators. This was quickly supplemented by detailed images from ground-based camera systems, and now, very commonly, by drones.

Images of the surface at and around a damaged area of composite material is insufficient to con-

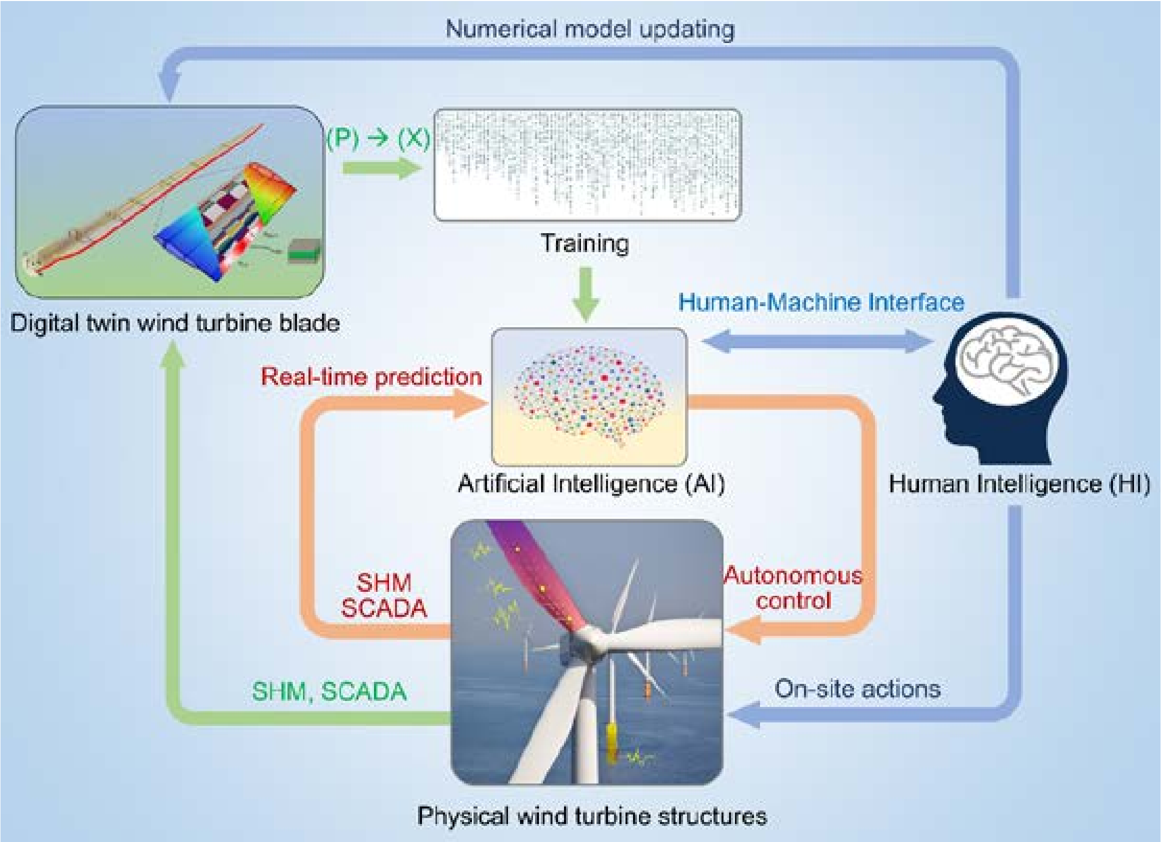

Figure 7.
Future wind turbine structures assisted by digital twins, artificial intelligence and human intelligence to achieve higher structural reliability. The artificial intelligence is trained by a digital twin, which makes predictions that aid the decision-making process and control the operation of the wind turbine in near real time. A supervisory human hierarchy is present to provide high-level strategies and perception-driven decisions, radical innovations and disruptive technologies to the entire wind-turbine system that are dynamic, lively and evolving over time, facilitated by real-time structural health monitoring and SCADA data. Adapted from [11].

clude the full extent and severity of damage that may be present within the structure. Sub-surface scanning inspections (such as ultrasonic inspection) reveal details about composite damage that are critical in order to evaluate the consequences for the future operation of the structure, as well as the cost and time required to repair the damage. These inspections can also uncover damage that cannot be seen by a technicians' eye or a drone camera. The detailed damage maps that can be generated by ultrasonically scanning a blade only ever provide a 'snap-shot' of the current state. Despite anticipated advances in automation, such scans are always likely to be demanding on time and resources. To obtain the improvements anticipated by the authors of this section, sensors embedded within the blade structure itself will be required. Thus, the monitoring of structural health can be roughly divided between ex-situ systems such as drones and in-situ systems such as sensors integrated into the structure. In the future, these two systems will be fully integrated and complementary.

By improving the understanding of material properties that control damage propagation, it will be possible to combine damage-tolerant structural design, monitoring systems, inspection techniques and modelling to manage the life-cycles of wind-turbine structures with the methodology proposed in [12]. Data provided by autonomous drones and blade-crawling robots inspecting and repairing wind-turbine structures generates detailed structural maps of damage and defect distribution within the material that allow structure-specific models to be generated. These autonomous scanning robots will interact with embedded sensors and transducers within the structures themselves, which also provide operation response data and alerts for significant changes in material and structure conditions as they occur.

It is in this massive increase of accurate, remote-access data regarding the condition and performance of every single wind-turbine structure in operation that the foundation for future improvements in affordability, reliability and sustainability are realized.

Conclusions and outlook

The key take-away from this chapter is the following:

A revolution towards better and smarter wind turbine structures is becoming feasible through a combination of several development leaps of key enabling technology, namely digitalization, artificial intelligence, advanced sensors, autonomous drone and robotic systems, and novel manufacturing methods. These next generation wind turbines will continuously operate at optimal asset performance with structural lifetimes exceeding those of present day wind turbines.

Structural testing will become even more important as a foundation for our in-depth understanding of complex structural behaviour in the physical world, based on which reliable, efficient numerical models can be developed and validated.

The numerical models and the physical tests will merge into one entity for structures in future made feasible by the recent advances in machine learning technology. Digital twins, AI and Structural Health Monitoring will take a key role in the transformation process from analogue to smart wind turbine structures. Human intelligence will be able to communicate with the wind turbine structures much the same way humanity already does with virtual personas in the digital world.

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