

A Human-Cyber-Physical System toward Intelligent Wind Turbine Operation and Maintenance

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Abstract: This work proposes a novel concept for an intelligent and semi-autonomous human-cyber-physical system (HCPS) to operate future wind turbines in the context of Industry 5.0 technologies. The exponential increase in the complexity of next-generation wind turbines requires artificial intelligence (AI) to operate the machines efficiently and consistently. Evolving the current Industry 4.0 digital twin technology beyond a sole aid for the human decision-making process, the digital twin in the proposed system is used for highly effective training of the AI through machine learning. Human intelligence (HI) is elevated to a supervisory level, in which high-level decisions made through a human-machine interface break the autonomy, when needed. This paper also identifies and elaborates key enabling technologies (KETs) that are essential for realizing the proposed HCPS.

Keywords: wind turbine; human intelligence; artificial intelligence; machine learning; digital twin; Industry 5.0



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1. Introduction to the Bigger Picture

Advancing wind turbine (WT) technology facilitates the attainment of several of the United Nations' Sustainable Development Goals (SDGs) by providing affordable and clean energy, fostering innovation for sustainable industrialization, and combating climate change [1]. In the future, the need for WT technology will reach a new level in order to support the global demand for reliable and sustainable energy.

The development of future WTs still faces many challenges. Imagine a large-scale renewable energy utility facility—a future offshore wind farm—comprising hundreds of interconnected wind turbines (WTs), each in the deca-megawatt range. Every WT of this wind farm is among the biggest and most complex machines in the world and is designed to produce energy consistently for its designated lifetime of 30 years in one of the harshest environments on this planet. Approaching one of these WTs more closely, we identify the rotor blades as the world's largest single component made from fiber composite materials, which, to date, have already exceeded the 100 m length mark and have a tendency for further growth. The rotor blades constitute one of the most critical components in the wind turbine since they directly interact with the outside environment, destined to carry the major load acting on the entire WT system.

The fate of a rotor blade is, to a considerable degree, already determined at the production site where it is produced with a set of individual and unique manufacturing defects and imperfections. Upon deployment, during its lifespan, the blade will suffer structural deterioration induced by a complex combination of severe dynamic loading, precipitation erosion, lightning strikes, and environmental effects (e.g., temperature fluctuations, humidity, and UV radiation). The mere fact that individual WT rotor blades exhibit such a

stark difference in structural performance during their service life is rooted in the diverse evolution of individual manufacturing defects under strongly varying local conditions on a wind farm. It is for this compelling reason that the blades ought to be treated individually while considering every blade's unique history. A direct consequence of treating blades individually is the evocation of a huge parameter space that needs to be controlled efficiently and with confidence to establish workable operation and maintenance (O&M) schemes.

Current state-of-the-art reactive O&M strategies for WT's foresee a scheduled maintenance interval of two to three years, in addition to unscheduled maintenance operations in situations of critical damage. A reactive O&M strategy with fixed inspection intervals, however, is rather costly and amounts to approximately 25–30% of the levelized cost of energy (LCoE). Therefore, increasing efforts are being made to shift from reactive to preventive schemes in order to reduce the cost of O&M.

In recent years, the digital twin (DT) concept has been introduced to wind turbines to advance preventive O&M technologies [2]. The DT in this work is stipulated as a high-fidelity numerical model that meticulously resembles the physical WT and consequently facilitates accurate predictions of the state of the physical turbine and its components. The idea of a DT dates back to the 1970s, when NASA initially implemented this concept in its Apollo space program [3]. After having sunk into oblivion, the DT has seen a renaissance driven by the soaring simultaneous advances in computational speed, numerical modeling techniques, and big data. In more recent works, the concept of a modern DT was outlined for application to aircraft and aerospace structures [4,5], and further reviews on the application of DT technology can be found in [6,7]. Studies [8–13] have discussed the development of a digital twin of wind turbines, structural health monitoring using Supervisory Control And Data Acquisition (SCADA) data and autonomous Unmanned Aerial Vehicles (UAVs), damage detection using an AI-assisted image process, and alternative algorithms for wind turbines. These studies [8–13] have contributed to bringing more autonomy, automation, and optimization into wind turbines, which increasingly grow in size and complexity.

As perceived in the wind energy sector, the prime purpose of a DT is to make accurate predictions of the structural health state of individual WT components, eventually enabling a reliable, accurate, and timely assessment of the entire WT. For this purpose, a DT needs to predict the evolution of the current damage status by considering the prevailing load history, environmental conditions, and manufacturing imperfections, among others. A DT, therefore, facilitates a consistent and continuous prediction of the structural performance of individually tagged components from the cradle to the grave. The true power of a DT, however, unfolds when it is coupled with a structural health monitoring (SHM) system that updates the DT with a live feed of the as-measured damage state, which allows predictions of the structural health state with unprecedented accuracy. The integration of DT technology and SHM systems, therefore, provides an opportunity for more cost-effective scheduling of maintenance intervals.

However, credible projections of wind turbine technology development outline an exponential increase in system complexity, rendering pure human-supervised O&M approaches insufficient and ultimately obsolete. In this situation, it is necessary to introduce more autonomy into the operation of the WT system. Similarly, for autonomous driving technologies [14,15], we envision future WT's having the ability to communicate and operate through machine brains that can make decisions autonomously in fractions of a second. These decisions will not only rely on information from local SHM systems but also depend on supplementary information gathered from other WT's on the wind farm. An individual WT will be warned by other WT's from the fleet about critical incidences, such as gusts arriving elsewhere at the wind farm, so that mitigation measures can be correctly anticipated and initiated in advance.

In this work, we propose a system stipulated as a human-cyber-physical system (HCPS) that is dedicated to the operation of tomorrow's large-scale wind farms. In such a system, the role of the DT is redefined: instead of just aiding human-based decision-making processes, it serves the purpose for training the AI through supervised machine learning.

In particular, the role of the human is elevated to a supervisory level. Human intelligence (HI) provides essential inputs to the system to make greater high-level decisions based on perception-driven strategies. The novelties of this work are as follows:

In our proposed system, the WT, SHM, DT, AI, and HI are fused together into one integral entity and work collaboratively to achieve higher levels of reliability, efficiency, and autonomy.

The AI controls the WT autonomously using real-time predictions—this is different from posterior control strategies that primarily relay on SCADA data and need constant human involvement.

- We propose using the DT to train the AI. Both physical data, such as those from SCADA and SHM, and simulated data from high-fidelity numerical models are fed into the AI, making the system more dynamic and robust than the current AI-assisted wind turbine systems that are typically data-hungry.
- In the proposed concept, the HI supervises the entire HCPS and collaborates with the AI by bringing radical innovations to each module and making high-level decisions to break the control autonomy, when deemed necessary.
- Projecting from the current state-of-the-art technologies, we identify and elaborate the KETs that are essential for the realization of the proposed concept.

2. Concept

WT technology has just arrived in the era of Industry 4.0, which is formed by integrating physical wind turbines and their digital twins into a cyber-physical system. The coupling between digital models and their physical counterparts is facilitated by the rapid development of several technologies, namely robust and sophisticated sensors, high-fidelity numerical models, computational power, machine learning, and information transfer technology, e.g., big data and the Internet of Things (IoT).

In the future, WT technology will enter a new paradigm in which the diverging strengths of HI and AI are integrated into a single system. Conceptually, AI should be able to make decisions with human-level precision or even beyond. However, the effectiveness of these decisions depends on the extent and quality of the training the AI receives. Quick decision making on an operational routine level is most effectively trained by solving a comprehensive set of numerical problems by using a DT. Decision making on a strategic level necessitates the long-term experience and empirical data of the HI gathered over several decades. That is, the different ever-evolving WT designs, the development of novel fabrication materials and manufacturing methods, the constantly changing weather conditions and market demands, etc., impose considerable uncertainty that may not be covered by the DT training space of the AI. For this reason, we advocate a semi-autonomous decision-making system in which the training of the AI should rely on a combination of DT technology and HI.

The cooperation between machines and humans is appreciated through human-machine interfaces in order to combine the strategic cognition of humans with nano-quick data processing speed and the consistency of machines. Networked sensor data interoperability enables humans to customize high-hierarchy decisions on a strategic level bespoke at scale. The central role of HI is a distinctive feature of Industry 5.0 compared to its predecessor according to researchers [16,17] and technology visionaries [18]. Inspired by the aforementioned pioneering work, this paper proposes an Industry 5.0 tier concept for the wind energy industry by building on existing Industry 4.0 technologies.

Figure 1 depicts the concept of the envisioned HCPS for WTs with an operational efficiency far beyond any current schemes. Human-machine cooperation evolves the current DT technology into a semi-autonomous system that uses supervised machine learning to base its decision-making process on previous experience and implements the optimal decision in quasi real time. This goal will be achieved by introducing three feedback loops that work simultaneously and collaboratively.

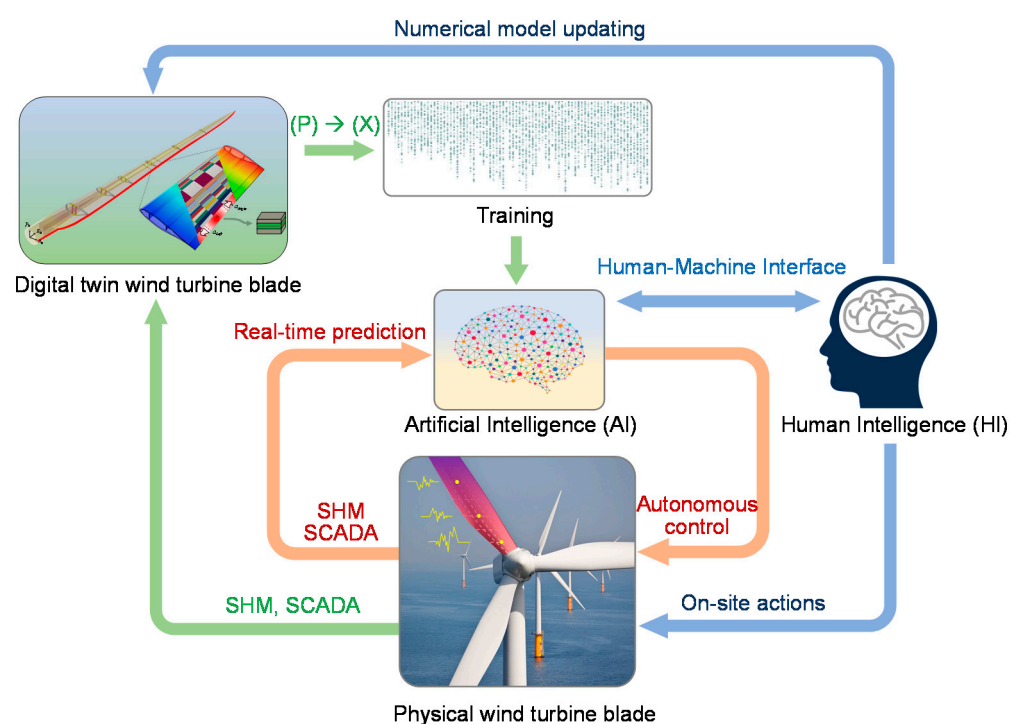


Figure 1. The human-cyber-physical system (HCPS) concept of future wind turbines in the Industry 5.0 era. The system comprises an AI (red loop) that directly controls the operation of the WT in quasi real time. The AI is trained by a DT that makes predictions that aid the decision-making process. A supervisory human hierarchy is present to provide high-level strategies and perception-driven decisions, radical innovations, and disruptive technologies to the system that is dynamic, lively, and evolving.

The red loop in Figure 1 illustrates that future WTs are embedded in an HCPS and operated by an AI using supervisory control and data acquisition (SCADA) in conjunction with SHM. The AI allows quasi real-time predictions and subsequently determines optimal operation parameters, which are fed back into the WT controller for instantaneous action. In this feedback process, the AI not only gathers data locally from one single WT but also collects far-field data from throughout the wind farm, e.g., approaching wind gusts or WT failure occurring elsewhere in the domain.

The green loop in Figure 1 depicts the training scheme of the AI, which is based on a continuous update of the damage state in the DT model through a live feed of SHM measurement data and keeps a medical journal of every individual rotor blade. Subsequently, using the SCADA feed, the DT predicts the evolution of the current damage for a set of key operational parameters to assess structural reliability, thereby creating a set of case samples. These case samples are consequently used to train the AI through a continuous recalibration of the parameter space. The computational efficiency of the DT facilitates the solution of a large number of damage evolution problems as a function of different WT control parameters, i.e., training samples. The AI seeks decisions that consider the specific preconditions prevalent in the individual blades and avoid certain load cases to decrease the likelihood of failure.

The blue loop in Figure 1 shows that the HI plays a higher-level supervisory role in direct communication with the AI through a human-machine interface to define the general superordinate directive. The HI plays an essential role in this system by providing innovation to the AI, DT, and physical WTs, such as improving and updating the mathematical formations of numerical models used by the DT and, if necessary, realigning the structural health state with the AI through on-site actions such as damage inspections. The active participation of HI in the HCPS enables a dynamic and creative process that constantly evolves and upgrades itself over time.

The inner workings of the DT shown in Figure 1 deserve a closer look and a separate treatise with a particular emphasis on the rotor blades. Figure 2 shows that the physical blade on the left-hand side is horizontally mapped to a DT on the right-hand side. Communication between the real world and the digital space is established using Industry 4.0 technologies such as the IoT, cloud computing, and big data. Three important stages throughout the life cycle of a blade are depicted in Figure 2, namely (i) manufacturing, (ii) operation and monitoring, and (iii) maintenance. Monitoring of the blade manufacturing process parameters is crucial for the identification and later tracking of damage throughout its lifetime. Therefore, the DT already comes into existence with the production of the blade containing manufacturing defects detected by automatized scanning procedures. The initial defects and manufacturing imperfections are stored in the archive of the DT uniquely associated with the particular blade. A numerical model of the as-built blade is created, and the initial defects are discretized. The DT is equipped with a computationally super-efficient probability-based numerical damage analysis tool capable of predicting the evolution of the current damage state stored in the archive. After the blade is endowed with SHM sensor systems and installed, it is linked to the DT, which receives a live feed of the structural health status (c.f. Figure 1). The archive of the DT contains information about the form, size, location, and type of the damage and is continuously updated throughout the blades' lifetime using SHM data and blade inspection data.

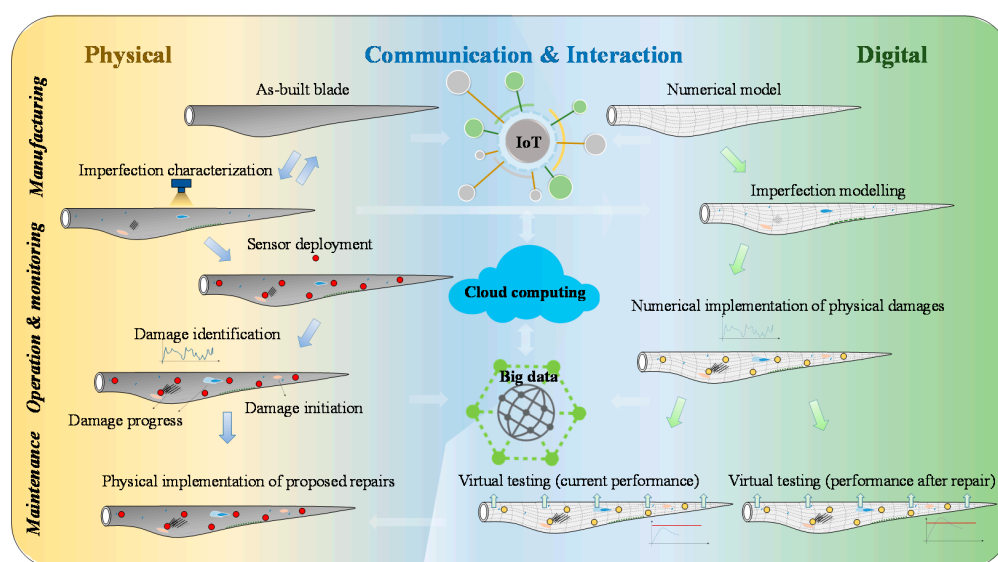


Figure 2. A digital twin of a wind turbine blade. The digital twin follows the entire life cycle of a wind turbine blade from manufacturing to operation to maintenance. With sensors deployed over the blade, in-service damages are monitored, allowing the numerical model to be continuously updated. The structural integrity can be assessed using the digital twin. Different scenarios can be simulated using virtual testing incorporated with damages, which facilitates reliable and accurate decision making for operation and maintenance. The physical blade and its digital twin are connected using Industry 4.0 technologies such as the Internet of Things, cloud computing, big data, etc., forming an integrated cyber-physical system.

3. Key Enabling Technologies (KETs)

As mentioned before, technologies like the IoT, AI, and machine learning play a major role in the HCPS. Complete coverage of all KETs and their interconnectivity involved in such complex systems is beyond the scope of this work due to the extensiveness of such an endeavor. Instead, only the KETs deemed particularly relevant to WTs and subject to a significant research and development demand are discussed in this section.

The first important KET on which we want to shed light pertains to sensor technology for SHM. Much like the nervous system continuously passing information of the state of

health (e.g., injuries, fatigue) to the brain, the sensors should detect the type, location, and size of damages in different subcomponents such as load-carrying spar caps, webs, and lift-generating surface panels. Efficient damage detection methods and sensor technologies have to be developed with the ability to cover large areas with reasonable accuracy. Along the lines of medical diagnosis, a suite of complementary sensing methods comprising internal embedded systems and nondestructive remote sensing technologies will be necessary to obtain a sufficiently complete picture of the structural health state. Embedded in-situ piezoelectric MEMS sensors, accelerometers, and Bragg refraction-based fiber optical sensors are among the most promising approaches. Ex-situ-based SHM systems based on measuring light in visual and infrared spectra will be implemented through stationary cameras or via autonomous drone inspection without the necessity to interrupt the WT operation. A recent work, the Automated QUALification of DAMages (AQUADA) system [19], uses thermography and computer vision to remotely detect and quantify structural damage below the surface based on the adiabatic heat generated in the material degradation process under cyclic loading. In this quantitative method, both data acquisition and analysis are performed in a single automated step, showing promising results for field applications.

The second important KET is called information translators in this work. In the development of an HCPS, it is crucial to bridge the gap between the physical world, such as SHM measurements, and the digital world, such as the DT, through data interpretation and information translation. First, SHM signals are predominantly an indirect measure of a physical process, which requires a reconstruction method for inverse problems such as magnetic resonance imaging (MRI) in medical diagnostics. That is, algorithms are necessary to interpret measured data and reconstruct surface cracks, skin/core debonding, and delamination from different types of complementary data such as thermal radiation, acoustics, vibration, strains, etc. Second, for the translation of the physical damage into a digital representation, robust and preferably automated tools must be developed. A first step dedicated to performing both interpretation and translation in a single process was taken with AUtomed Damage INspection and Identification from images (AUDIN) [20]. AUDIN uses digital image processing technology to obtain the physical characteristics of typical macroscale damages from thermography, ultrasound, or shearography and subsequently represents these physical characteristics, e.g., crack size and crack shape, in the finite element model of the DT in an automated way.

The third important KET concerns high-performance numerical damage prediction models. Training of the AI requires the DT to make swift predictions of the damage state evolving in the blade. The stochastic nature of predicting damage evolution in large-scale rotor blades demands probabilistic analysis approaches in which individual simulations are repeated for a variation of the governing parameters. This process craves for computationally super-efficient numerical models that can simulate multiple damage sites under complex loading situations. One of the most notorious bottlenecks in the simulation of damage propagation in large-scale rotor blades, even on supercomputers, is the clash of different characteristic length scales: numerical models must capture damage mechanisms at the microscale, i.e., 10^{-4} – 10^{-3} m, and simultaneously simulate structural response at the macroscale, i.e., 10^1 – 10^2 m. This entails computationally heavy finite element models that render impractical computation times when conventional numerical approaches are adopted. FASTIGUE [21], a recently developed method, is a computationally super-efficient approach dedicated to simulating discrete crack growth in large-scale structures under high-cycle fatigue. FASTIGUE gains its efficiency by essentially decoupling the computationally heavy fracture mechanics analysis from the crack growth prediction, contributing to the development of this KET.

AI will continue to be an important KET, playing a central role in the operation of future WTs. Recent advances in AI technology showed promising results in many fields by providing human-level performance. A recent work [22] proved that deep learning approaches can successfully train AI to detect and locate surface damage on rotor blades at approximately 87% accuracy, even for rare damage types from image-based drone in-

spection. These models illustrated strong performance on the images, which were spatially correlated and represented very high-dimensional data. For critical condition detection in rotor blades, the AI can deal with low-dimensional data, reducing the complexity of the training set, which usually requires thousands of annotated or previously seen examples with relevant indicators. A huge amount of data must be provided for the AI to absorb and learn. By using DT technology in conjunction with numerical methods like FASTIGUE and through extensive measurements from sensor collectives, abundant data can be gathered for the AI to operate effectively.

Another important KET is the human–machine interface enabling the HI to interrupt AI-based decision making by intervening with human intuition in order to break the autonomy, when deemed necessary. This is still an open question, however, and to some degree solvable by restricting the HI interference actions to only critical conditions based on the confidence level in prediction reported by the AI. The machine learning process is treated as a black box without interpreting the relationship and causality of the features or data points. To incorporate a semi-autonomous HCPS, it is crucial to investigate the underlying physics of measurement data and to map the impact on the decision-making process, which is usually beyond a machine’s capability. Therefore, the capability of the HI to make expert decisions based on understanding and perception should be incorporated into the AI in order to get the most reliable and accurate results.

The aforementioned KETs work together to realize the proposed system. The relationship among these KETs is depicted in a block diagram shown in Figure 3.

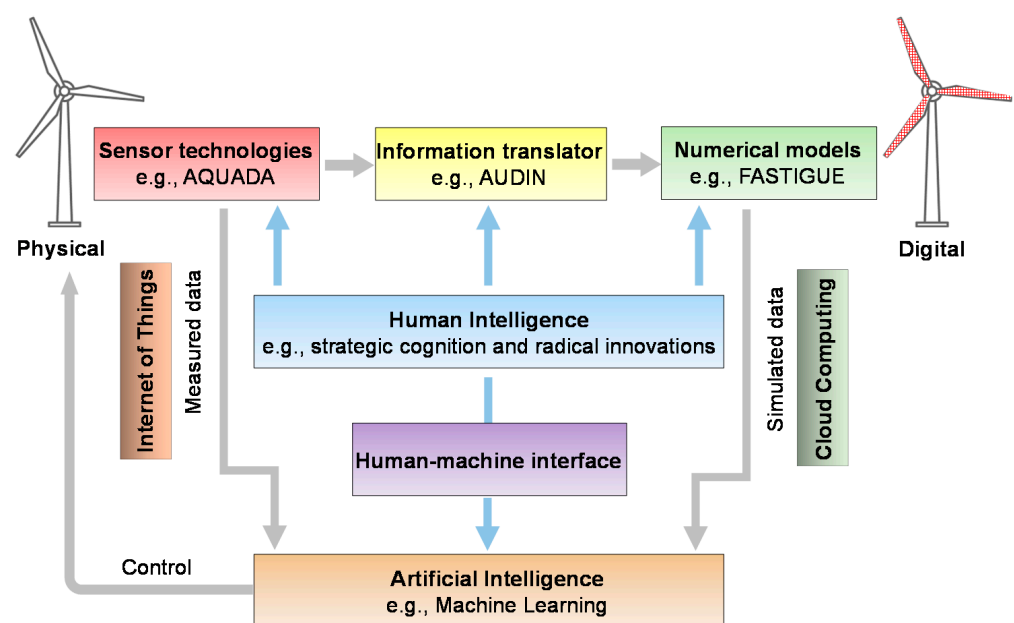


Figure 3. The block diagram of the proposed HCPS showing the essential KETs and their relationships. A streamlined process bridges the physical world and the digital domain using AQUADA, AUDIN, and FASTIGUE. The process is assisted by the Internet of Things (IoT) and cloud computing to generate, store, and analyze data. Both physically measured data and numerically simulated data are fed into the AI, which controls the physical wind turbine semi-autonomously. Human intelligence sits in the center of the system, providing radical innovations to other KETs, e.g., cheaper and more robust sensors or faster and more accurate numerical models. In addition, human intelligence interacts with the AI through the human–machine interface, providing high-level designs based on strategic cognition to break the autonomy when certain cases cannot be handled effectively by the AI.

4. Outlook

The aforementioned KETs are just a starting point and have not yet reached the required technological readiness level necessary to sustain an HCPS, as outlined in this work.

Nevertheless, the relevant KETs in other sectors such as mass production, the automotive industry, and the aerospace industry are considerably more advanced compared to the wind industry. The advancement in these sectors with extensive efforts carried out by leading high-tech organizations, such as NASA, the U.S. Air Force, Airbus, Tesla, IBM, and Huawei, continues to provide a driving force for translating, adapting, and implementing similar technologies into the wind energy sector. Incorporating the advancement of these KETs into the proposed HCPS will enable the realization of more autonomous and smart wind turbines in the future.

Projecting Industry 4.0-to-Industry 5.0 technology leaps into the distant future bears a good deal of uncertainty with respect to developmental periods and the precise way of realization. Nevertheless, technological advancements, particularly in sensor technology, smart materials, drone technology, AI, the IoT, and quantum computing, continue to grow at an incredible speed, so much so that Industry 5.0 can already be seen on the horizon at the beginning of the third decade of the 21st century (see Figure 4). An HCPS for WTs will likely become operational and continue to mature in the coming one to two decades, contributing to the United Nations' SDGs in affordable and clean energy, innovating for sustainable industrialization, and combating climate change, which will eventually benefit all humanity.

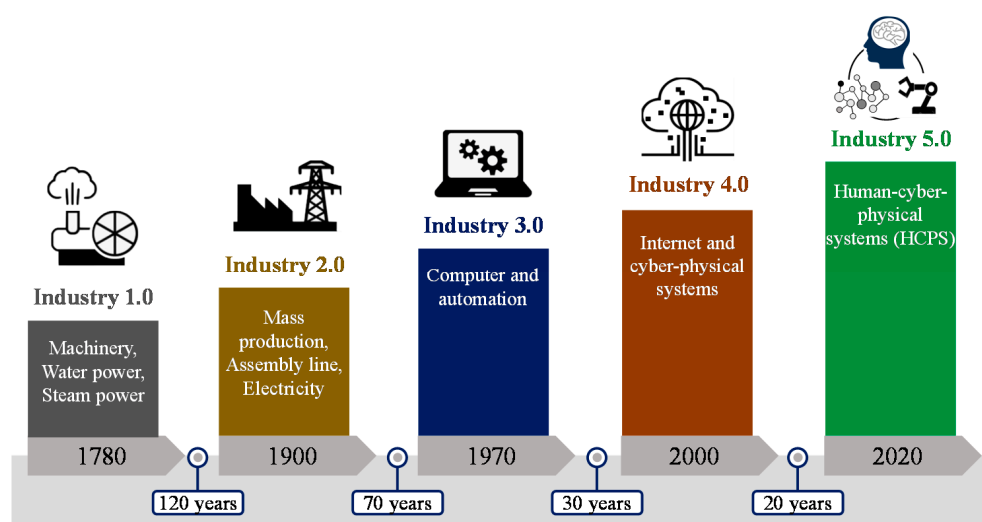


Figure 4. Industrial revolutions in human history. The first industrial revolution used water and steam power to mechanize production. The second industrial revolution used electricity for mass production. The third industrial revolution used computers to automate production. The ongoing fourth industrial revolution uses information technologies to connect the physical world and the digital world. The fifth industrial revolution is expected to bring the human back to the center of operation through a human-cyber-physical system for value creation. Two observations are worth noting. The first one is that the transition time from one industrial revolution to the next has become considerably shorter, manifesting the rapid development of technologies in the modern era. The second one is that from the second to the fourth industrial revolution, there was a big leap in conceptually new technologies; nevertheless, the next industrial revolution is still based on its predecessor. Projecting from these historical observations suggests that a human-cyber-physical system will be the most likely topic of the fifth industrial revolution in the coming one to two decades.

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Abbreviations

HCPS	human-cyber-physical system
AI	artificial intelligence
HI	human intelligence
SDG	Sustainable Development Goal
WT	wind turbine
DT	digital twin
SHM	structural health monitoring
KET	key enabling technology
IoT	Internet of Things
SCADA	supervisory control and data acquisition

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