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An advanced structural health monitoring IoT platform for offshore wind turbine blades

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Abstract. Wind energy is renewable and is an essential ingredient in the move towards carbon neutrality and net zero emissions Compared with onshore wind turbines, offshore wind turbines generally experience higher wind speed, thus producing more electricity. However, the increasing dimensions of turbine blades and demands in economic requirements of wind turbines' life cycles, together with the harsh marine environment, including high winds, wave-induced vibrations, sea and rain corrosion and erosion, pose challenges for structural integrity, operational efficiency and maintenance cost. This paper presents a novel Internet of Things (IoT) platform for structural health monitoring (SHM) of the offshore wind turbine's key components, the wind turbine blades, taking the design and manufacturing of turbine blades into account. This research focuses on developing a comprehensive, real-time monitoring system that utilises advanced sensor networks and edge computing, empowering advanced predictive algorithms to strengthen in-time maintenance of turbine blades, improving operational efficiency and reducing maintenance cost.

Keywords: Offshore wind turbines / IoT platform / structural health monitoring / blade monitoring / QRS sensor / cloud database / wind energy / renewable energy

1 Introduction

Wind energy has contributed significantly to electricity production in both the UK and the EU, as these countries are committed to achieving carbon neutrality. Figure 1 [1] illustrates the estimated impact on CO_2 reduction from 2008 to 2030, as the deployment of wind turbines increases. It is clear from the figure that wind energy will continue to play a growing role in producing green electricity and reducing emissions.

The linear motion of the wind causes the wind turbine blades to rotate, this then drives the gearbox and the generator to output electrical power. The aerodynamic characteristics of the turbine blades determine the amount of energy extracted from the wind. In this sense, the turbine blades are critical components of large-scale offshore wind turbines. In addition to normal wear and tear due to ageing, in-service turbine blades may also suffer potential damage from erosion, corrosion, debris and lightning strikes. Damage or failure of a turbine blade can limit the functionality of the entire wind turbine, negatively affecting energy production, as well as the overall economic performance during the whole life cycle.

In recent years, the Internet of Things (IoT) has significantly transformed the interconnectivity of many industries, enabling real-time data visualisation and thus improving operational efficiency [2]. This paper presents a novel IoT platform targeting structural health monitoring (SHM) of offshore wind turbine blades. The research focuses on developing a real-time system that integrates advanced sensor networks, edge computing, cloud databases, predictive algorithms, and operational and maintenance personnel in a unified platform, to collectively enhance turbine blade maintenance, improve power generation efficiency, and significantly reduce maintenance-related costs.

As the demand for green energy sources continues to intensify, the need for more powerful wind turbines increases. In response, the wind energy industry has shifted towards large-scale turbines, which are capable of harnessing greater amounts of wind energy. Figure 2 shows the offshore wind turbine deployment, in terms of the radius of rotor and power output capacity, which clearly indicates the rising trends over the past 20 years. Generally

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larger-diameters rotors sweep a more extensive area, thereby capturing a larger volume of wind and therefore generating increased electricity. Even in regions with relatively low wind speed conditions, longer blades are capable of harnessing a more substantial portion of the available wind resources, compared to shorter blades. The ability to capture energy efficiently at reduced wind speeds expands the potential deployment to wider geographical locations.

Wind turbine blades endure complex operational loads —including aerodynamic, gravitational, and inertial forces —as well as environmental stresses such as temperature fluctuations, moisture exposure, icing, and lightning strikes. These factors collectively contribute to structural degradation mechanisms such as fatigue, delamination, surface erosion, and crack propagation, which compromise blade integrity over time. Given their critical role in energy conversion and system stability, blades are pivotal to the overall performance and longevity of wind turbines. Consequently, early damage detection is essential not only to ensure operational safety but also to optimise maintenance planning, minimise downtime, and mitigate repair costs. Structural health monitoring SHM thus carries significant economic and safety implications, serving as a proactive strategy to extend asset lifespan and enhance the reliability of wind energy systems.

The use of IoT technologies facilitates condition-based maintenance, a more efficient alternative to traditional maintenance strategies for these structures that rely on periodic inspections and reactive repairs. Instead of performing maintenance activities at predetermined intervals, condition-based maintenance schedules tasks are based on the actual condition of the blades, consider the severity of structural damage, resource availability, and associated costs. This not only reduces unnecessary maintenance activities but also ensures timely responses to critical issues, thereby optimising resource allocation and reducing operating costs.

In addition, the integration of IoT with cloud computing and big data analytics provides a scalable solution for managing the vast amounts of data generated by the sensors. Cloud-based platforms can store and process historical sensor data, and the hardware and software resources required can be increased or adjusted as needed. This enables operators with comprehensive reports and actionable insights into the health of the turbine blades. This platform enhances decision-making and enables remote monitoring, which is particularly advantageous for offshore wind farms located in challenging and less-accessible environments.

Turner [13] presented the application of Fibre Bragg Grating (FBG) sensors for SHM of wind turbine blades. FBG sensors, as fibre optic sensors to sense strain, stress, deflection, vibration and temperature, are well known for their immunity to electromagnetic interference and suitability for harsh environments. Surface-mounted and embedded FBG arrays monitored strain and temperature during design validation and in-service operation. A high-speed interrogator enabled real-time data acquisition at 1 kHz with 1 $\mu\varepsilon$ strain resolution, which is outstanding compared to performance of conventional electronic strain gauges. Field tests demonstrated the system's ability to detect mechanical behaviour under static, dynamic, and varying wind loads. The authors emphasise the advantages of FBG sensors, including multiplexing capability and integration into composite materials, concluding their effectiveness in optimising blade design and enabling predictive maintenance.

Avdelidis [14] reviewed infrared thermography (IRT) as a non-destructive evaluation (NDE) method for glass-reinforced polymer (GRP) wind turbine blades. Both passive and active thermography techniques (e.g., pulsed, lock-in, vibrothermography) are analysed, alongside advanced signal processing methods such as pulsed phase thermography (PPT) and principal component thermography (PCT). IRT enables rapid, large-area inspection to detect defects such as delamination, debonding and Fibre cracking. While IRT is cost-effective and non-contact, its limitations include shallow depth penetration (<5 mm) and sensitivity to environmental conditions. Case studies illustrate its use in adhesive joint inspection and fatigue testing. The authors highlight ongoing efforts to standardise IRT and develop robotic in-situ applications for offshore wind farms, positioning it as a critical tool for blade quality assurance and structural evaluation.

Lim [15] proposes a novel wireless SHM system where energy harvesters (EHs) convert blade vibrational strain into electrical energy to power RF transmitters. The timing of RF pulses, linked to energy accumulation rates, serves as a damage indicator. A triple-redundancy algorithm compares pulse intervals from sensors on three blades to detect stiffness loss (e.g., from matrix cracking). Using strain data from a 2.5 MW turbine, simulations showed that a 20 per cent increase in harvested energy (simulating damage) reduced pulse intervals, detectable via threshold-based analysis. The system addresses challenges of remote monitoring and power constraints, leveraging EH self-sufficiency and wireless communication. Experimental validation with piezoelectric MFC harvesters confirmed feasibility, though future work is needed to refine damage localisation and threshold selection. This approach offers a scalable, low-maintenance solution for blade SHM.

Choi *et al.* [16] presented an experimental study on active-sensing SHM techniques for wind turbine blades using piezoelectric transducers. The paper investigates two high-frequency methods—Lamb wave propagation and frequency response functions (FRFs)—to detect incipient damage in composite blades. Experiments conducted on a section of a CX-100 blade demonstrate that properly configured piezoelectric sensor arrays can capture subtle changes in wave characteristics (e.g., attenuation and phase shifts) when damage is introduced. The study discusses key considerations such as excitation frequency selection, sensor placement, and the limitations due to material damping, thereby providing guidelines for designing effective SHM systems for wind turbine blades.

Van Dam and Bonda [17] explored the use of acoustic emission (AE) techniques for real-time damage monitoring in wind turbine blades. The study employs pencil lead breaks as a standardised reference AE source to simulate damage events on unidirectional glass-fibre-reinforced-polymer plates. By analysing the elastic waves generated

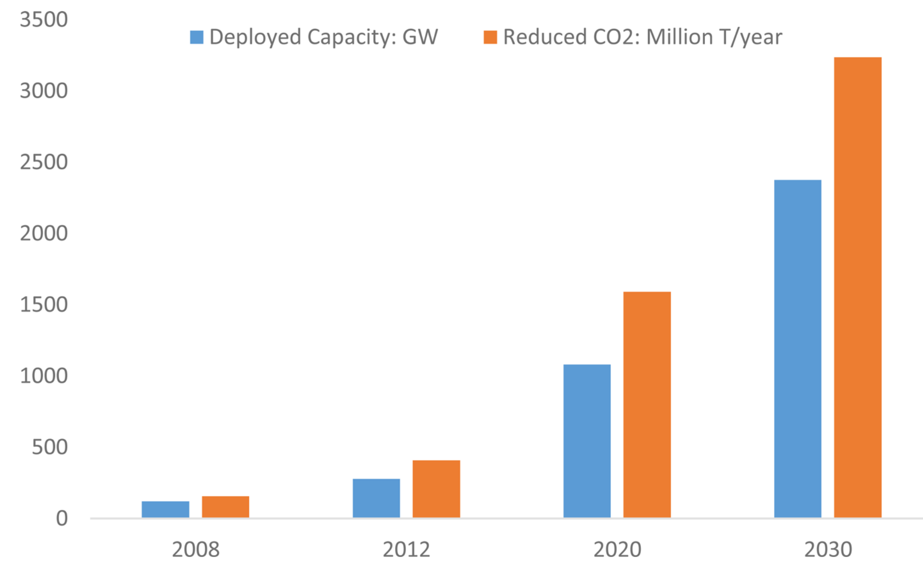

Fig. 1. Wind turbine deployment and corresponding CO2 emission reduction [1] trend.

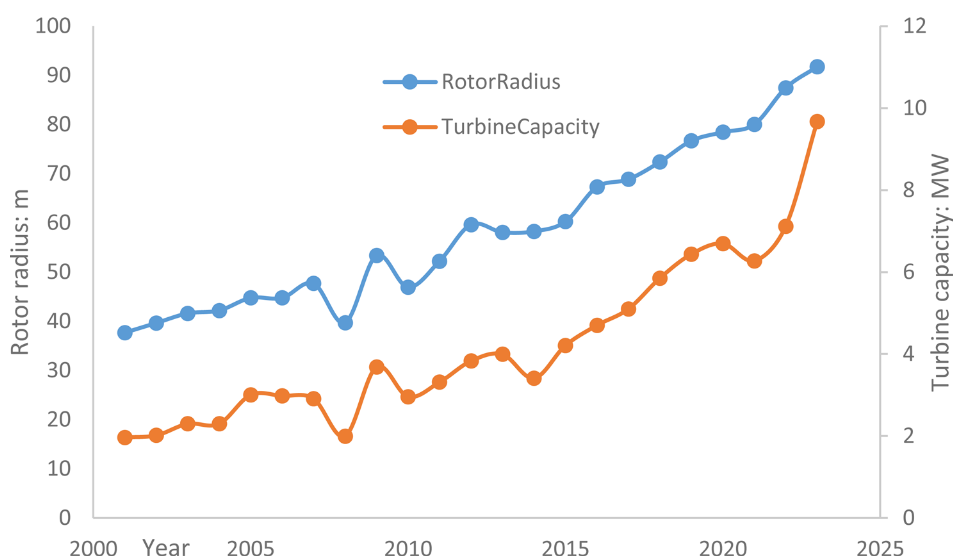

Fig. 2. Worldwide average offshore wind turbine capacities since 2000 [4].

during these events—with a focus on Lamb wave dispersion characteristics—the authors apply the Gabor wavelet transform to extract dispersion curves, revealing insights into wave speeds, mode behavior, and attenuation in composite materials. The findings underscore the potential of AE monitoring as an online SHM tool capable of detecting and localising damage before catastrophic failures occur, thus offering a pathway toward more proactive maintenance strategies in the wind energy sector.

Carnero *et al.* [18] introduced an integrated system that combines a motorised telescope with machine learning for the external inspection of wind turbine blades. The system leverages deep convolutional neural networks to automatically detect and classify surface defects from high-resolution images. Key components include a mobile application for image capture, a motorised mount that facilitates automated scanning, and an edge computing node that processes the images in real time. Experimental validation in a wind farm setting reports high accuracy (around 97 per cent for label predictions and 90 per cent for bounding box localisation), illustrating the system's potential to reduce inspection times and enhance safety by minimising the need for manual, high-risk inspections.

Pacheco-Chérrez and Probst [19] demonstrated a novel vibration-based structural health monitoring approach for wind turbine blades using Operational Modal Analysis (OMA) under natural wind excitation. Their methodology combines the NREL FAST tool with ANSYS Workbench to generate and analyse acceleration time series caused by rotationally sampled wind turbulence. Using the Frequency Domain Decomposition algorithm, they successfully extracted modal parameters from these acceleration signals

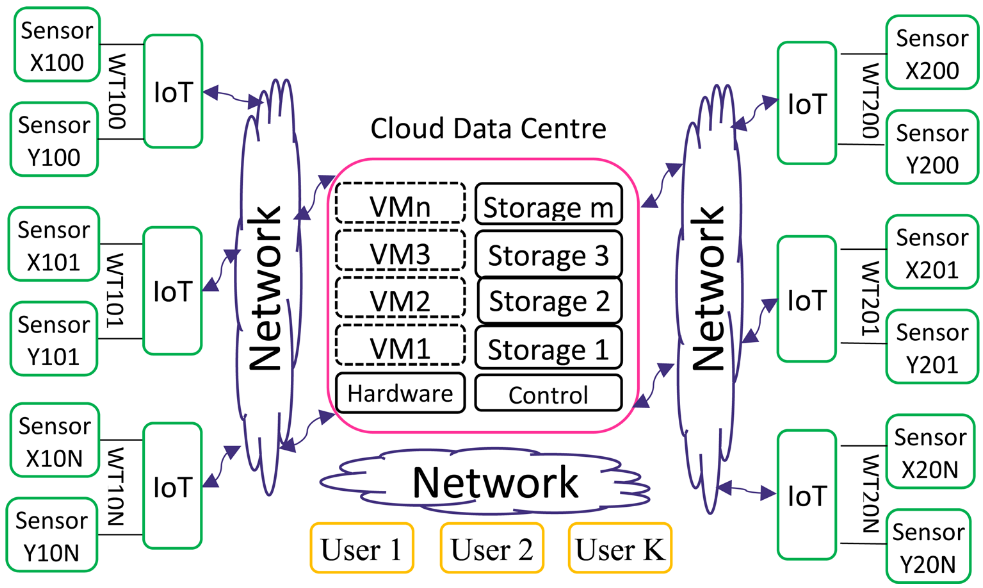

Fig. 3. Overview of IoT platform. WT100,101...WT10N, WT200, WT201...WT20N: wind turbines installed with SHM sensors, VM1, VM2, VM3...VMn: virtual machines/computers by virtualisation technologies, User 1, User 2... User K: authorised users with access to SHM sensor data, usually by internet.

and applied the Mode Shape Difference metric to detect and precisely locate longitudinal crack damage. Their approach is significant as it requires only eleven sensors along the blade and relies entirely on natural wind excitation without artificial inputs, potentially enabling cost-effective structural health monitoring for wind turbine components while maintaining detection reliability.

Wind turbine blades exhibit large, often curved geometries that necessitate innovative sensor design and strategic placement to ensure accurate monitoring. Moreover, continuous data acquisition results in extensive datasets, which calls for advanced methodologies in data processing, storage, and interpretation. Additionally, scaling up wind turbine deployments further complicates hardware configuration and software development. In response to these challenges, this paper investigates an IoT platform for SHM as a comprehensive solution, featuring quantum resistive sensors (QRSs) and a highly flexible and scalable cloud-based database.

This paper introduces the structure and manufacturing of offshore wind turbine blades in Section 2, then the architecture of the structure health monitoring IoT platform is presented in Section 3. In Section 4 the testing procedures and results are reported.

2 IoT platform architecture

Figure 3 depicts the architecture of an IoT platform designed for structural health monitoring of offshore wind turbine blades. Sensors embedded within the turbine blades are interfaced with IoT hardware which processes, packages, and transmits sensor data to a cloud data centre over the network. The data is then stored in the cloud-based database, accessible to users for analysis of the structural health of individual turbine blades. Advanced analytical technologies, including digital twin models and machine learning algorithms, can be applied to this data, enabling continuous monitoring of structural integrity, optimal operational recommendations, and timely maintenance predictions.

A prominent feature of modern IoT platforms is their inherent scalability, which is crucial for accommodating the dynamic demands of wind turbine blade health monitoring systems. Specifically, the platform's scalability extends to the number of installed wind turbines, the overall database size, and the number of simultaneous users. IoT devices, including those embedded within wind turbine blades, connect to cloud data centres via high-speed networks and operate as relatively autonomous units. This modularity ensures that the addition or removal of a single device or sensor generally does not disrupt the entire system. Such resilience is enabled by a robust software architecture that leverages virtualised computing, storage, and network resources, allowing the cloud database to be expanded seamlessly without necessitating a rebuild of existing facilities [5,7].

From a hardware development and deployment standpoint, cloud platforms offer virtualised environments that obviate the need for dedicated physical servers. Autoscaling mechanisms dynamically allocate or decommission resources based on real-time demand, ensuring that computational capacity and storage are always in line with the current sensor data influx. Containerisation technologies, such as Docker coupled with orchestration frameworks such as Kubernetes, further enhance this flexibility by allowing individual microservices to be deployed, updated, and scaled independently. These features not only streamline hardware resource management but also reduce reliance on physical infrastructure, thereby lowering both capital expenditure and the risks associated with hardware obsolescence.

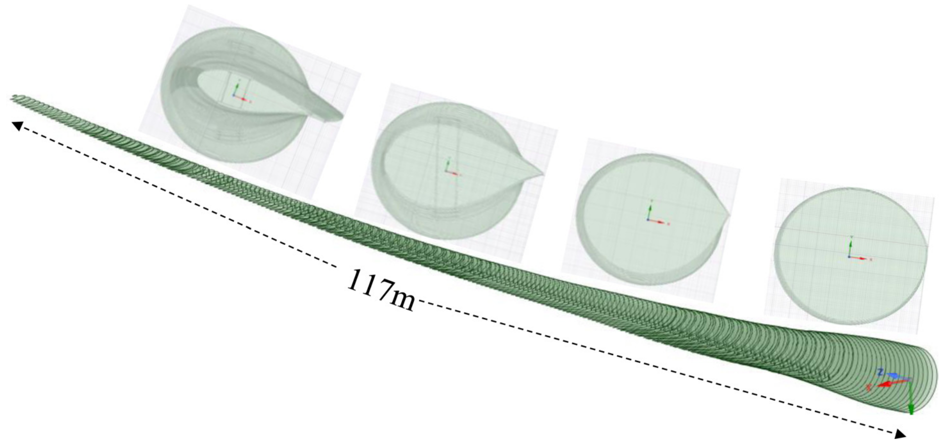

Fig. 4. Wind turbine blades designed for 15 MW capacity with complicated section profiles.

On the software development front, modern IoT platforms are designed around agile DevOps practices, including Continuous Integration/Continuous Deployment (CI/CD) pipelines and Infrastructure as Code (IaC) approaches. These methodologies facilitate the rapid deployment of updates, bug fixes, and new features while ensuring minimal downtime and consistency across the platform. The separation of applications into microservices allows for isolated scaling of critical data processing functions, which is essential for handling both real-time and batch processing of large sensor datasets. Technologies such as Apache Kafka for stream processing and Apache Spark for distributed computation enable the efficient ingestion, analysis, and interpretation of high-velocity data streams, ensuring that actionable insights, such as early indicators of blade degradation, are delivered in a timely manner.

Furthermore, the cloud's scalability extends to data processing and user access. Authorised users, regardless of their geographic location, can access high-fidelity data as long as they have a network connection, with the cloud infrastructure supporting virtually unlimited concurrent users [3]. This pervasive accessibility fosters collaborative research and operational efficiency across multiple stakeholders.

By consolidating servers and optimising resource usage through virtualisation, cloud platforms significantly reduce both the energy consumption and the physical footprint of the infrastructure. Fewer servers mean lower power and cooling requirements, translating into reduced utility costs and a smaller carbon footprint, a critical factor in meeting the renewable energy sector's sustainability goals [6]. Additionally, the gradual, progressive deployment of wind turbines, often a multi-year endeavour, is well supported by the scalable nature of IoT platforms. This enables capital investments to be distributed over time, thereby lowering initial costs and mitigating potential operational risks.

In summary, the scalability and flexibility inherent to cloud-based IoT platforms are pivotal in addressing the challenges associated with hardware provisioning, software deployment, and large-scale data processing in wind turbine blade health monitoring systems. These capabilities ensure that as sensor networks expand and data volumes grow, the system remains robust, efficient, and economically sustainable.

2.1 Wind turbine blade structure

Integral to its performance is the blade structure, which must endure and efficiently capture wind energy at diverse conditions while minimising structural stress and fatigue. These blades are engineered to optimise aerodynamic performance and structural integrity. The complexity of designing such large-scale blades requires a thorough understanding of materials science, aerodynamics, and structural dynamics. Figure 4 illustrates the design of 15 MW capacity wind turbine blades, featuring 117 meters in length, maximum 5 metres in diameter and complicated structure design [8]. Overall the diameter of the blades is gradually reducing from blade root to blade tip while the airfoil is varying from a circle shape to an oval.

Innovative materials and manufacturing techniques are central to the development of these turbine blades. Advanced composites, such as carbon fibre and glass fibre, have become critical in ensuring the necessary strength-to-weight ratio. These materials not only enable the construction of longer, stiffer blades but also contribute to overall turbine efficiency by reducing rotational inertia. Figure 5 gives the details of a typical section of the blade structure, including relatively thick spars and webs to increase stiffness and strength, while lightweight requirements are prioritised in other parts of the section. For parts where high strength and stiffness are preferred, such as Spar_ss and Spar_PS, which are load-bearing regions, multi-ply carbo fibre and glass fibre are stacked up with different angles. For parts such as TE_SS_filler and TE_PS_filler, relatively low-density foam and glass fibre are placed.

The manufacturing of 15 MW scale wind turbine blades is a highly sophisticated process that merges advanced engineering with precision fabrication techniques. The manufacturing of the blade proceeds through several key stages, including material preparation and layup, resin infusion and curing.

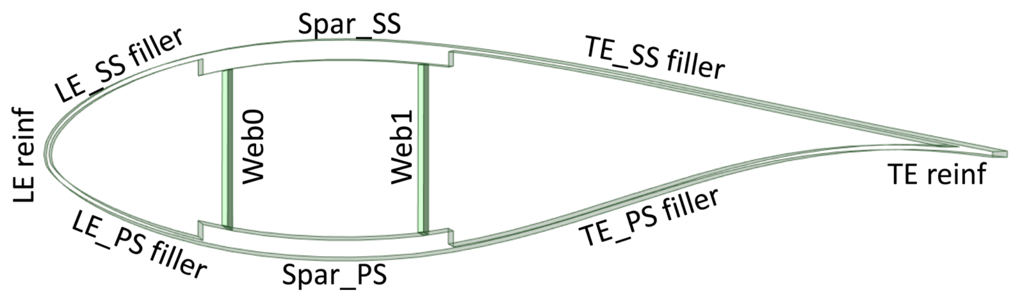

Fig. 5. Typical section of the composite wind turbine blade. LE reinf: leading edge reinforcement, LE_SS filler leading edge suction side filler, Spar_SS: suction side spar, TE_SS filler: trailing edge suction side filler, TE reinf: trailing edge reinforcement, TE_PS filler: trailing edge pressure side filler, Spar_PS: pressure side spar, LE_PS filler: leading edge pressure side filler.

Fig. 6. Composite stack-up (a) fillers including LE_SS_filler, LE_PS_filler, TE_SS_filler and TE_PS_filler. Glass_UD: unidirectional glass fibre, Glass_biax: biaxial glass fibre, Gelcoat: coating for UV protection. (b) Spar_SS and Spar_PS. Carbon_UD: unidirectional carbon fibre.

The initial phase is to prepare the composite materials, where fibrous materials are carefully arranged to form a pre-designed layup pattern. This pattern is critical in determining the blades' final properties, dictating areas of enhanced strength and flexibility. The layup process may involve manual or automated placement of the fibres onto a mold, depending on the complexity and scale of the design.

Figure 6a shows the stack-up of composite plies of fillers used in the turbine blade design. Compared with the materials in Figure 6b for Spar_SS and Spar_PS, relatively light and economical materials such as foam and glass fibre were selected, while the core of spars is made of stronger glass fibre.

Once the fibre arrangement is complete, the next step involves the infusion of a resin into the fibre layers. This phase is crucial for achieving the desired material properties and structural integrity.

Following resin infusion, the blade undergoes a curing process, where it is exposed to controlled temperatures to solidify the resin matrix. This phase is essential for transforming the layered composite into a rigid, load-bearing structure. The curing process is meticulously controlled to ensure uniform resin hardening, preventing defects such as warping or incomplete bonding.

2.2 Sensor network

As shown in Figure 7, a heterogeneous sensor network, including QRS, accelerometer and acoustic emission sensors, is utilised to capture the turbine blades' health-related data. The QRS sensors, namely humidity QRS (hQRS), temperature QRS (tQRS) and strain QRS (sQRS), are installed in the wind turbine blades, to monitor moisture, temperature, and strain respectively at the designated locations. QRS can be manufactured using the same resin as the composite material, allowing them to be cured to a comparable degree of crosslinking. This approach ensures that the thermal and mechanical properties of the sensor are fully homogeneous with those of the composite matrix. The strain sensitivity of QRSs can be finely tuned by adjusting their composition or altering processing conditions, offering customisable sensitivity levels. Furthermore, QRSs achieve heightened —environmental sensitivity, particularly to nano-deformations — due to their percolated sensing architecture, which promotes tunnelling conduction [9]. The QRS sensors are so thin and resin-compatible that they can be integrated into the composite material without damaging the inter-ply adhesion. Figure 8 illustrate the manufacturing process of spars with embedded QRS sensors.

The accelerometer and acoustic emission sensors are used to detect cracking, delamination, debonding, and impacts affecting the blade [11,12]. According to the load under different working conditions, the sensitivity of the sensor at different positions is determined by structural analysis [10]. Sensors installed in the optimal locations reflects the critical structure damage status and progression.

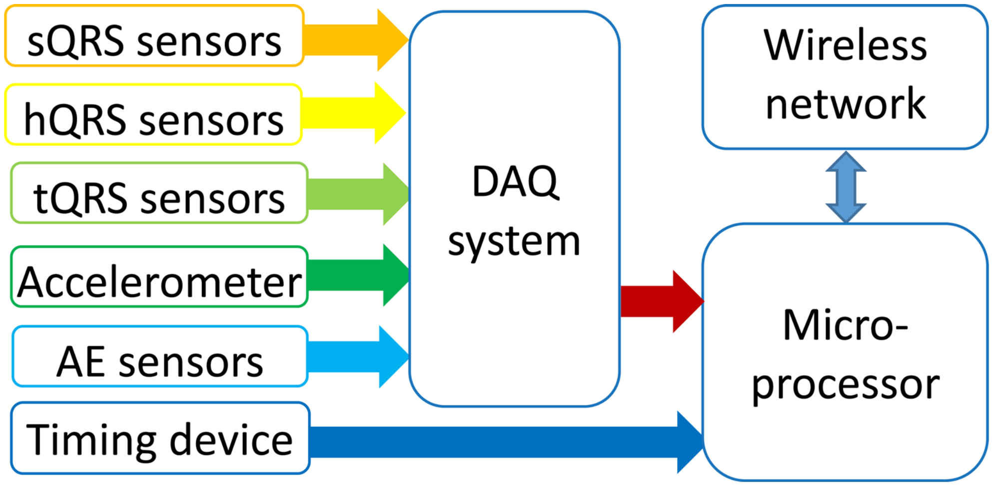

Fig. 7. Sensor network connection to micro-processor. sQRS sensors: strain QRS sensors; hQRS: humidity QRS; tQRS: temperature QRS; AE sensors: acoustic emission sensors.

2.3 IoT hardware

The DAQ system interfaces with the QRS, accelerometer and AE sensors to pre-process raw sensor data, thereby minimising network traffic. Pre-established thresholds are defined within the system to trigger alarms, allowing for timely intervention when necessary. Subsequently, the DAQ system transmits the processed data to the microprocessor, which then relays it via a wireless network to the cloud data centre, as illustrated in Figure 8. This approach not only reduces the data volume transmitted to the central cloud centre but also enables prompt detection of potential issues, minimising dependency on continuous high-bandwidth connectivity.

2.4 Real-time data visualisation

The platform features a powerful data visualiation and alert system that provides real-time dashboards and notifications to stakeholders. This includes a clean and easy-to-use interface that displays sensor readings and predictive analytics results. The alert system ensures that critical issues are flagged immediately to alert and assist relevant personnel respond quickly, thereby reducing catastrophic failures.

The real-time cloud database stores the relevant sensor data frames in chronological order. It supports elastic storage and provides sensor data to users from different platforms (such as Windows and Linux computers and mobile phones) over the Internet. The GUI in Figure 9 visualises the sensor data and briefly summarises the blades' status, helping operators and users to quickly understand the current status and historical conditions of the wind turbines and take prompt action if required.

3 IoT platform testing

The IoT platform was tested thoroughly to assess whether it functions as designed and to ensure its suitability for in-service structural health monitoring of offshore wind turbine blades. Both the hardware and software were tested.

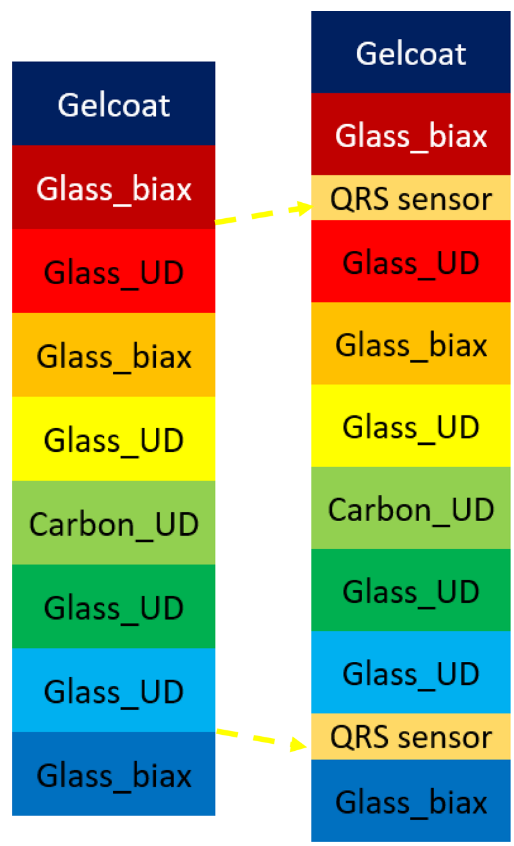

Fig. 8. Spars with embedded QRS sensors. Left: without QRS sensor; right: with QRS sensor.

3.1 Hardware function testing

Figure 10a is the main hardware unit consisting of a microprocessor, a wireless network adaptor and related

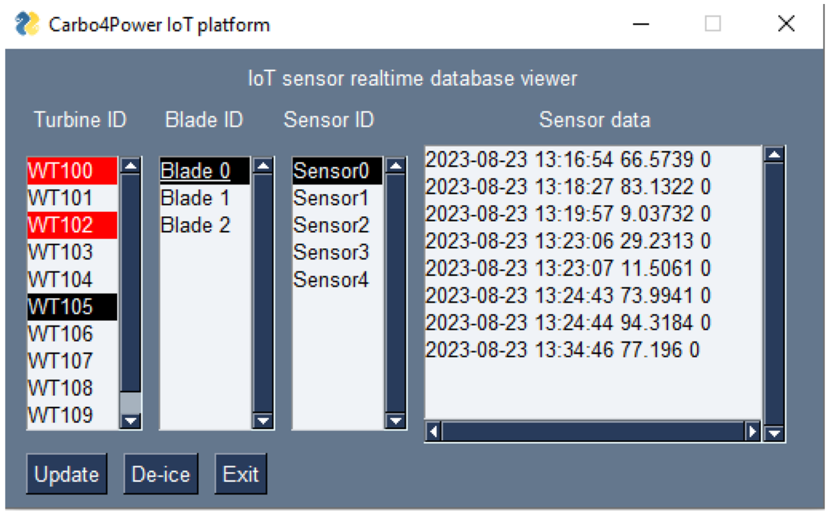

Fig. 9. GUI for real-time sensor database visualisation.

Fig. 10. IoT main hardware unit with micro-processor and wireless network. (a): photo of IoT hardware unit; (b) testing of Ethernet network; (c) testing of wireless network.

accessories, which are packed in a black box. An Ethernet port is attached to the main unit, which is convenient for local debugging and testing.

When the main unit was powered on and the Ethernet cable was unplugged, the Ethernet port lights went out; when the Ethernet cable was plugged in, the amber light on the Ethernet port turned on and the yellow light started to flash when there was network traffic passing through the Ethernet port; the yellow light remained on when the traffic stopped. The main unit obtained successfully IP address and netmask from the network gateway, as shown in Figure 10b.

After connecting to the WIFI network, the IP address and DNS were obtained. Figure 10b shows the IP address of the wireless network was obtained correctly. Pinging the google.com server returned information on server's IP address, response latency and Time to Live (TTL), as shown in Figure 10c. The remote IP address of the server (domain name) was correctly resolved, indicating the DNS server was configured and working. The ping results confirmed that the wireless network hardware was functioning and able to communicate with the remote servers without losing packets.

The timing device real-time clock was able to keep synchronised with the network time server. Figure 11a shows the time and date, which was the same with the time in the laptop when checked.

The hardware platform was tested to run more than 7×24 hours to check the stability. The test ran from 8 August 2023 to 11 October 2023, lasting more than $9 \times 7 \times 24$ days.

3.2 Software function testing

A DAQ simulator was developed that provides an interface similar to the physical DAQ system with a remote database. When accessing the DAQ simulator, the IoT platform software returned the correct date and time from the DAQ simulator, as shown in Figure 11.

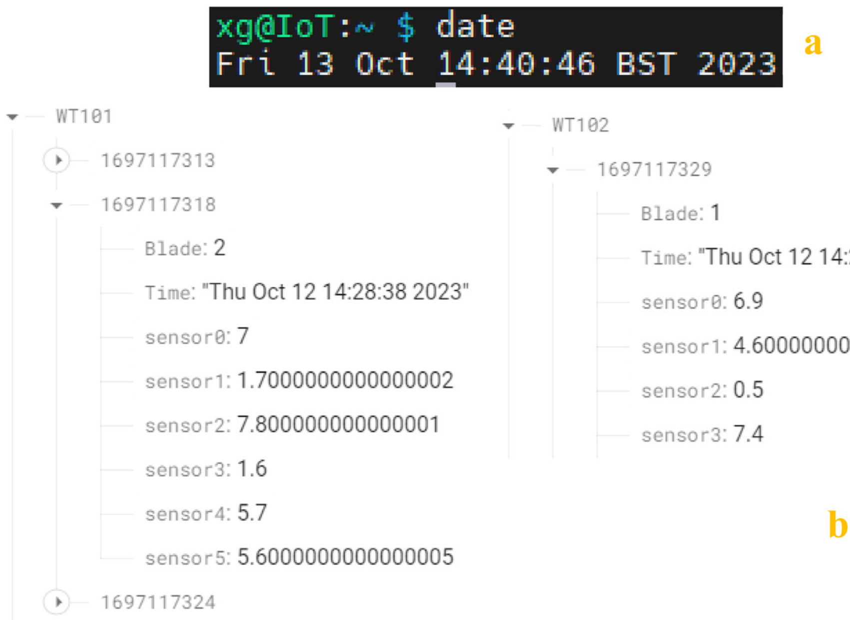

Figure 11. Evaluation of access to cloud database.

The real-time cloud database was interfaced wirelessly and could be read and modified by the IoT platform. The IoT platform software was able to read all the sensor data and refresh the sensor data when new data became available from the DAQ simulator, as shown in Figure 11b. The data are arranged in a tree-like structure and can be easily read by human being and machines for automation. For instance, WT101 represents the identification number of wind turbines; the 1697117318 timestamp when sensor data were collected, which can be verified by the data content labelled as "Time"; Blade label identifies the blade number in the wind turbine, which can vary from 0 to 2 in this study. Other data contained are sensor specific.

The main functions of the GUI included display of the sensor data according to the wind turbine label, blade number and sensor number. The selected sensor was verified as shown in Figure 9. When there was an alert from the DAQ simulator, the corresponding wind turbine was marked in red, to highlight the alarm to the users and operators.

More experimental testing results are available in papers and reports regarding the QRS sensors' performance [9] and non-destructive sensing techniques (AE) [20].

4 Concluding remarks & future work

This study makes a significant contribution to the field of wind turbine blade structural health monitoring by developing and validating a comprehensive IoT platform that integrates advanced QRS sensor technology with cloud-based intelligent data analysis. Specifically, this work bridges critical gaps in the existing literature by illustrating how the embedding of QRS sensors within turbine blades, coupled with a scalable cloud-based architecture, can reliably deliver real-time SHM solutions.

In addition, the platform demonstrates exceptional scalability, not only in terms of accommodating an increasing number of wind turbines and vast database sizes, but also in managing virtually unlimited data traffic. This scalability is achieved through cloud-based robust technologies of virtualised hardware resources and agile software deployment practices, which together support dynamic resource allocation and real-time data processing.

Future work will further evaluate the IoT platform with a primary focus on enhancing data analysis techniques. Additionally, since cloud database operations—including data storage, transmission, and processing—are governed by international regulations, a detailed investigation into their compliance and operational implications will be considered.

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Conflicts of interest

The authors of this paper declare no conflict of interest.

Data availability statement

This article has no associated data generated and/or analyzed / Data associated with this article cannot be disclosed due to legal/ethical/other reason.

Author contribution statement

Conceptualization: X. Zhou. Y. Tian, Y. Qin, C. Charitidis, T. Milickovic and S. Termine; Research Methodology and Software Realisation: X. Zhou; Validation: X. Zhou, Y. Qin, C. Charitidis, T. Milickovic and S. Termine; Manuscript Preparation: X. Zhou; Manuscript Review and Editing: X. Zhou and Y. Qin; System Visualisation: X. Zhou and Y. Tian; Project Supervision and Administration: Y. Qin, C. Charitidis, T. Milickovic and S. Termine.

References

1. Global Wind Energy Council, *Wind power is crucial for combating climate change*, https://gwec.net/wp-content/uploads/2012/06/Wind-climate-fact-sheet-low-res.pdf (accessed October 10, 2023)
2. M. Soori, B. Arezoo, R. Dastres, Internet of Things for Smart Factories in Industry 4.0: A review, Internet Things Cyber-Phys. Syst. 3 (2023) 192–204
3. S. Henning, W. Hasselbring, Benchmarking scalability of stream processing frameworks deployed as microservices in the cloud, J. Syst. Softw. 208 (2024) 111879.
4. A. McCoy, W. Musial, R. Hammond, D. Mulas Hernando, P. Duffy, P. Beiter, P. Pérez, R. Baranowski, G. Reber, P. Spitsen, Offshore Wind Market Report: 2024 Edition, National Renewable Energy Laboratory, Golden, CO, NREL/TP-5000-90525, 2024.
5. C. Pahl, Containerization and the PaaS Cloud, IEEE Cloud Comput. 2 (2015) 24–31
6. L.A. Barroso, J. Clidaras, U. Hölzle, The Datacenter as a Computer: An Introduction to the Design of Warehouse-Scale Machines, 2nd ed., Morgan & Claypool Publishers, 2013.
7. J.W. Rittinghouse, J.F. Ransome, Cloud Computing: Implementation, Management, and Security, CRC Press, 2009.
8. S.J. Scott, P. Greaves, T. Macquart, A. Pirrera, Comparison of blade optimisation strategies for the IEA 15 MW reference turbine, J. Phys. Conf. Ser. 2265 (2022) 032029
9. A. Lemartinel, M. Castro, O. Fouche, J.C. De Luca, J.F. Feller, Impact and strain monitoring in glass fibre reinforced epoxy laminates with embedded quantum resistive sensors (QRSs), Compos. Sci. Technol. 221 (2022) 109352.
10. M. Inalpolat, C. Niezrecki, Acoustic sensing-based operational monitoring of wind turbine blades, J. Phys. Conf. Ser. 1452 (2020) 012050.
11. S. Ding, C. Yang, S. Zhang, Acoustic-signal-based damage detection of wind turbine blades—A review, Sensors 23 (2023) 4987
12. M.A. Fremmelev, P. Ladpli, E. Orlowitz, N. Dervilis, M. McGugan, K. Branner, A full-scale wind turbine blade monitoring campaign: Detection of damage initiation and progression using medium-frequency active vibrations, Struct. Health Monit. 22 (2023) 4171–4193
13. A. Turner, T.W. Graver, Structural monitoring of wind turbine blades using fibre optic Bragg grating strain sensors, in: T. Proulx (Ed.), Experimental Mechanics on Emerging Energy Systems and Materials Vol. 5, Springer, New York, 2011, pp. 231–237
14. N.P. Avdelidis, T.-H. Gan, Non-destructive evaluation (NDE) of composites: Infrared (IR) thermography of wind turbine blades, in: Woodhead Publishing Series in Composites Science and Engineering, 2013, pp. 634–650.
15. D.-W. Lim, S.C. Mantell, P.J. Seiler, Wireless structural health monitoring of wind turbine blades using an energy harvester as a sensor, presented at 32nd ASME Wind Energy Symposium, AIAA 2014-1395, January 201
16. S.-W. Choi, K.M. Farinholt, S.G. Taylor, A. Light-Marquez, G. Park, Damage identification of wind turbine blades using piezoelectric transducers, Shock Vib. (2014) Article ID 430854, 9 pages.
17. S. Ding, C. Yang, S. Zhang, Acoustic-signal-based damage detection of wind turbine blades—A review, Sensors 23 (2023) 4987
18. A. Carnero, C. Martín, M. Díaz, Structural health and intelligent monitoring of wind turbine blades with a motorised telescope, presented at 21st IEEE Int. Conf. Mach. Learn. Appl. (ICMLA), Nassau, Bahamas, 2022, pp. 105–112.
19. J. Pacheco-Chérrez, O. Probst, Vibration-based damage detection in a wind turbine blade through operational modal analysis under wind excitation, Mater. Today **56**, (2022) 291–297
20. F.P. Garcia Márquez, M. Papaelias, V.L. Jantara Junior, Introduction to non-destructive testing and condition monitoring techniques in wind energy, in: *Wind Energy Engineering*, Elsevier, 2023, pp. xxi–xxii.

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