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Fostering open science through a digital open innovation platform - structural health monitoring case study

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Abstract. Open science and open innovation practices based on digital platforms can help address the lack of digital maturity and data sharing in the wind energy sector. Some previous efforts to introduce open science and open innovation practices in wind energy have been based around the WeDoWind project, which fosters data sharing through the organisation and documentation of open challenges. In this work, a two-phase Design Thinking approach is introduced for transforming WeDoWind from a platform for documenting and managing challenges (phase 1) to an open innovation ecosystem for fostering open science and open innovation in wind energy (phase 2). The feasibility of the new open innovation ecosystem for fostering open science and open innovation in wind energy is then evaluated. The feasibility study involves first defining the scope and goals, defining KPIs for the evaluation, carrying out the case study, ending with an evaluation of the KPIs. The case study itself involves defining case study KPIs, choosing the case study topic, setting up and managing a WeDoWind challenge (The ASCE-EMI Structural Health Monitoring for Wind Energy Challenge), and then evaluating the case study KPIs. The challenge goal is to detect three fault events with the highest possible accuracy. Five solutions submitted to the challenge include the PyMLDA Open-Code method, a Health Index Monitoring with Variational Autoencoders method, an Unsupervised Event Classification using K-Means Clustering method, and an Unsupervised damage detection method using a feature selection framework. The results show that the case study could be successfully used for comparing and evaluating different fault detection methods. The overall feasibility is rated as "Medium," due to the strong governance, clear regulation, and promising scalability potential.

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However, further progress is required to make it financially sustainable, to ensure adoption of the results in the sector, and to ensure community engagement to reach the critical mass necessary for self-sustaining growth.

1 Introduction

1.1 Open science and open innovation

The hurdles currently facing the wind energy sector are often complex and of transdisciplinary nature (Veers et al., 2019; Kirkegaard et al., 2023). At the same time, it is known that a lack of data and knowledge sharing is an issue (Clifton et al., 2023; Barber et al., 2023c; Marykovskiy et al., 2024), and digitalisation was recently named by ETIPWind as one of five Megatrends in wind energy technology[1]. The lack of data maturity in the sector results in inefficiencies in handling and creating insights from the large volume of data produced throughout the life-cycle of a wind energy project. For example, operational data formats are not consistent across different software solutions used to monitor and operate wind farms, and key metadata are often lacking (Marykovskiy et al., 2024).

Open science and open innovation practices can help overcome these hurdles. Open science can be defined as "transparent and accessible knowledge that is shared and developed through collaborative networks" (Vicente-Saez and Martinez-Fuentes, 2018). In an attempt to foster open science, many journals and funding agencies now encourage, require, or reward some open science practices. Therefore, many resources have emerged to help researchers implement them. In Europe, the European Open Science Cloud supports the development of many resources, including tools developed by the EOSC Science Clusters such as the ENVRI Knowledge Hub[2].

Open innovation describes the opening of innovation processes in order to involve external stakeholders such as customers, experts and partner organisations in the development of new products, services or technologies (Som et al., 2014). It has been shown to be crucial for tackling the multifaceted challenges of the energy transition, which span technical, economic, and social domains (Dall-Orsoletta et al., 2022). Open innovation can be driven through digital platforms, which can overcome geographical and organisational boundaries, enabling the exchange of knowledge in global networks (Som et al., 2014). Digital open innovation platforms use digital technologies to promote collaborative processes. They make it easier for companies and projects to develop innovative ideas, collect data and implement solutions. The effectiveness of such platforms has been demonstrated by various studies. For example, one study showed that 64-77% of companies that use open innovation approaches profit from a combination of internal and external stimuli to successfully implement their innovative projects (Som et al., 2014). Companies that combine external and internal sources of knowledge increase the success rate of new products by up to 19% compared to purely internal approaches. Another example of a digital open innovation platform is Kaggle, a platform that organises data science competitions. Studies show that a high level of engagement can be achieved through competition formats and targeted incentives (Mollick, 2014). Crowd-funding platforms such as Kickstarter are similarly successful, with projects that interact with their target group at an early stage achieving up to 65% higher success rates. Despite these suc-

[1]https://etipwind.eu/wp-content/uploads/files/publications/20241104-Etipwind-factsheet-five-megatrends.pdf
[2]https://envri.eu/

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cesses, however, digital platforms also face specific challenges. The protection of intellectual property, long-term user loyalty and the continuous further development of technological standards are decisive factors, and statistics show that up to 50% of newly founded platforms fail within the first five years, often due to a lack of user loyalty or ineffective monetisation strategies (Mollick, 2014).

In wind energy, efforts to introduce open science and open innovation practices include the development of semantic artefacts for representing wind energy knowledge (such as the IRP classification of activities WEAVE, the IEA Wind Task 43 lidar ontology, and the IEA Wind Task 43 WRA Data Model, summarised in Section 6.2 in (Marykovskiy et al., 2024)), an analysis of the findability, accessibility, interoperability and reusability (FAIRness) of wind energy data (Barber et al., 2024), and the introduction of the WeDoWind platform for running, managing and documenting wind energy data science challenges by the lead author of this present paper (Barber et al., 2022, 2023b, a; Barber and Ding, 2024) in an attempt to improve data sharing. However, recent examinations of digital maturity in wind energy highlight the need for holistic, community-based solutions for bringing together different open science and open innovation activities, and aligning them within and beyond the wind energy sectors (Marykovskiy et al., 2024; Clifton et al., 2023; Barber et al., 2023c). Therefore, in this work, we aim to transform WeDoWind from a platform for documenting and managing challenges to an open innovation ecosystem for fostering open science and open innovation in wind energy.

1.2 This contribution

The goal of this paper is to apply a Design Thinking approach to transform WeDoWind from a platform for documenting and managing challenges to an open innovation ecosystem for fostering open science and open innovation in wind energy, and then to test its feasibility via a case study. The case study involved planning and managing the ASCE-EMI Structural Health Monitoring for Wind Energy Challenge. After introducing the Design Thinking approach in Section 2, the feasibility study approach is described in Section 3, and then the results of the feasibility study are presented in Section 4. Finally, the conclusions are drawn in Section 5.

2 Design Thinking approach

A Design Thinking approach (Pearce, 2020) with two phases was applied to transform WeDoWind from a platform for documenting and managing challenges to an open innovation ecosystem for fostering open science and open innovation in wind energy. Each phase consisted of the steps “Empathise”, “Define”, “Ideate”, “Prototype” and “Test”, as shown in Fig. 1.

Phase 1 (Jan. 2022 to Dec. 2024) involved first defining the problem of the lack of data sharing in the sector, and then interviewing members of the community to understand their needs (“Empathise”). These results allowed a solution to the problem to be defined (“Define”), which was to develop a platform for enabling asset owners (who own data, and need state-of-the-art data analytic solutions) to publish data and a WeDoWind challenge (a specific problem statement). Each challenge then gets solved by data scientists and researchers (who are looking for data to train their state-of-the-art data analytic solutions), providing both sides with a mutual benefit. Several ideas for implementations were developed and assessed (“Ideate”), ending

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up with a prototype for a digital platform called Relight ("Prototype") together with the company Stacker Group. This was launched with an initial challenge together with the company EDP in March 2022. Since then, eight different challenges have been launched and run, some still running and several already documented (Barber et al., 2022, 2023b; Barber and Ding, 2024; Barber et al., 2024). The prototype has been continuously improved, using participant surveys and inputs from Advisory Board meetings ("Test").

Phase 2 (Jan. 2025 onwards) started by combining the inputs from participants and Advisory Board members from Phase 1 with knowledge gained on the topics of data maturity and digitalisation in IEA Wind Task 43 (Clifton et al., 2023; Marykovskiy et al., 2024) ("Empathise"). This allowed several improvements to the Phase 1 prototype to be defined, and made it clear that exploiting the full value of data requires a larger ecosystem, and should include people developing information models, publishing data and code, and developing tools and guidelines for open data and code. This allowed a general concept for Phase 2 to be defined, called the WeDoData Blueprint (Fig. 2) ("Define"). The WeDoData Blueprint is focused on four communities of people, which have many synergies and overlaps that are exploited in the Blueprint: (1) The Information Modelling Community, for developing information models such as data models, schemas, taxonomies, and ontologies; (2) The Open Data and Code Community, for working on guidelines and best practice documents for publishing open code and data; (3) The Collorative Problem-Solving Community, for sharing data and knowledge via challenges; and (4) The Data Users' Community, for developing best practice documents and other resources for using data and code. The results of the work in these communities are fed into the WeDoData Portals: the Schema Publishing Portal, the Ontology Publishing Portal, the Open Data Portal, the Open Code Portal and the Job Portal. The challenges can be run on a separate dedicated data science platform, and the whole community can be managed on a communication platform. The Blueprint provides a suggestion for a structure for any data sharing community of any size and in any sector. Based on the WeDoData Blueprint, possible digital platforms for the "communication platform" were investigated, by defining requirements and assessing the level of fulfillment of various commercial and in-house options ("Ideate").

This led to the creation of a Phase 2 prototype, which uses the commercial software Mighty Networks ("Prototype")[3]. This prototype was built and launched for the wind energy sector as the new WeDoWind open innovation ecosystem in January 2025, together with a new website[4]. The four running challenges were transferred from Relight to the Collaborative Problem-Solving Community on the WeDoWind platform and were continued seamlessly in the Open Data Exploration space, the Data Science for Wind Energy space, the RTDT space and the EAWE Test Turbines Committee space. Additional spaces for completed challenges were created (the EDP Challenges space and the WinJi Challenges space). In the Information Modelling Community, working groups for the development of a Wind Energy Domain Ontology, an Operations Ontology, TIM-Wind, and the Digital Twins Taxonomy were created. These initiatives are all connected to IEA Wind Task 43, which is led by the main author and acts as a digital transformation catalyst by driving open collaboration within and beyond the wind community to deliver insights, recommendations, standards and tools. In the Open Data and Code Community, a space for the RDA Wind Energy Community Standards Working Group, which is currently creating a recommendation for improving FAIR data

[3]https://community.wedowind.ch/
[4]https://www.wedowind.ch/

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maturity in wind energy. In the Data Users' Community, a space for Data Enginering in Wind Energy and a space for the IEA Wind Task 43 Data User Group was created. For the Portals, links were including to external platforms. For the Schema Publishing Portal, a link to the tool Octue Strands is provided, which is a tool for curating and publishing JSONSchema[5]. For the Ontology Publishing Portal, a link to the TechnoPortal[6] is provided, which is an ontology repository for the engineering and technology domain, and includes formalisations of many wind energy semantic artefacts. For the Open Data Portal, a list of known open data sources is given. For the Open Code Portal, a list of known open code sources is given. A concept for a combined Open Knowledge Hub is currently underway. The Job Portal enables participants to post job adverts and searches. Furthermore, solutions for covering the running costs of the platform are being tested. Ideas include donations, sponsoring, paying for challenges, certificates, paying for extra features, paying for trending options and monetisation through recruiting.

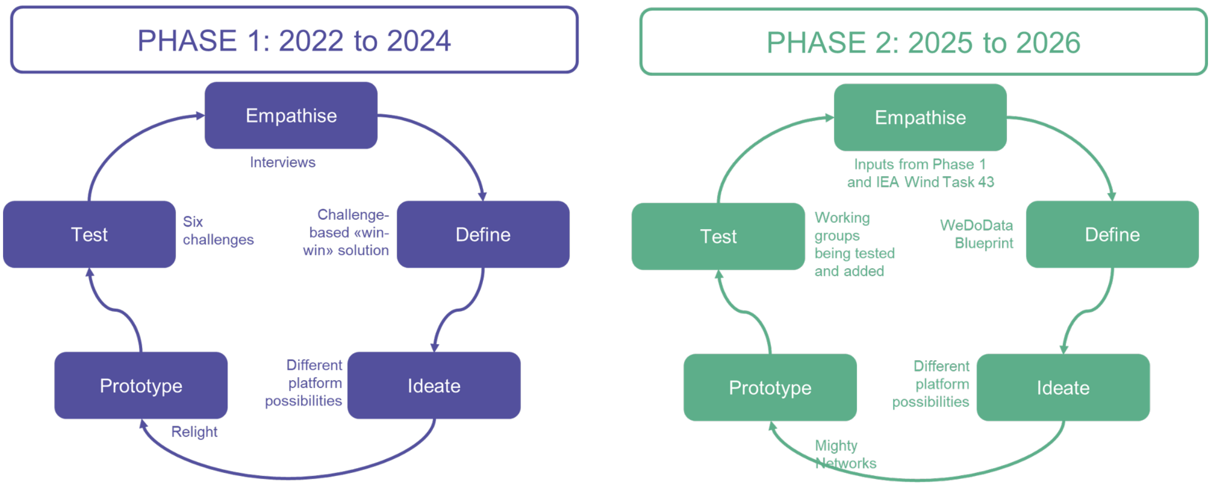

Figure 1. The design process of the WeDoWind ecosystem.

[5]https://strands.octue.com/
[6]https://technoportal.hevs.ch/

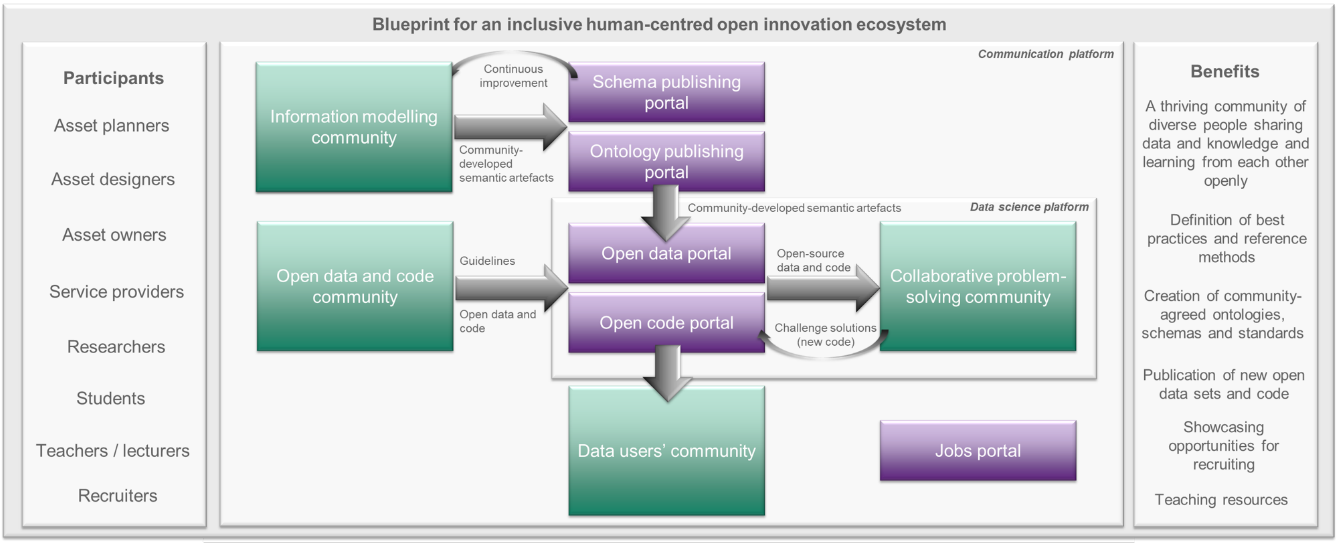

Figure 2. Overview of the WeDoData Blueprint.

3 Feasibility study

The feasibility study was carried out as illustrated in Figure 3. After defining the scope and goals of the feasibility study in step (1), the feasibility study KPIs for the evaluation were defined in step (2) and then a case study was carried out in step (3), ending with the feasibility study evaluation in step (4).

The case study itself involved defining case study KPIs in step 3(a), choosing the topic in step 3(b), setting up the case study in step 3(c), managing it in step 3(d) and then evaluating it in step 3(e). These steps are described in more detail in the next sections.

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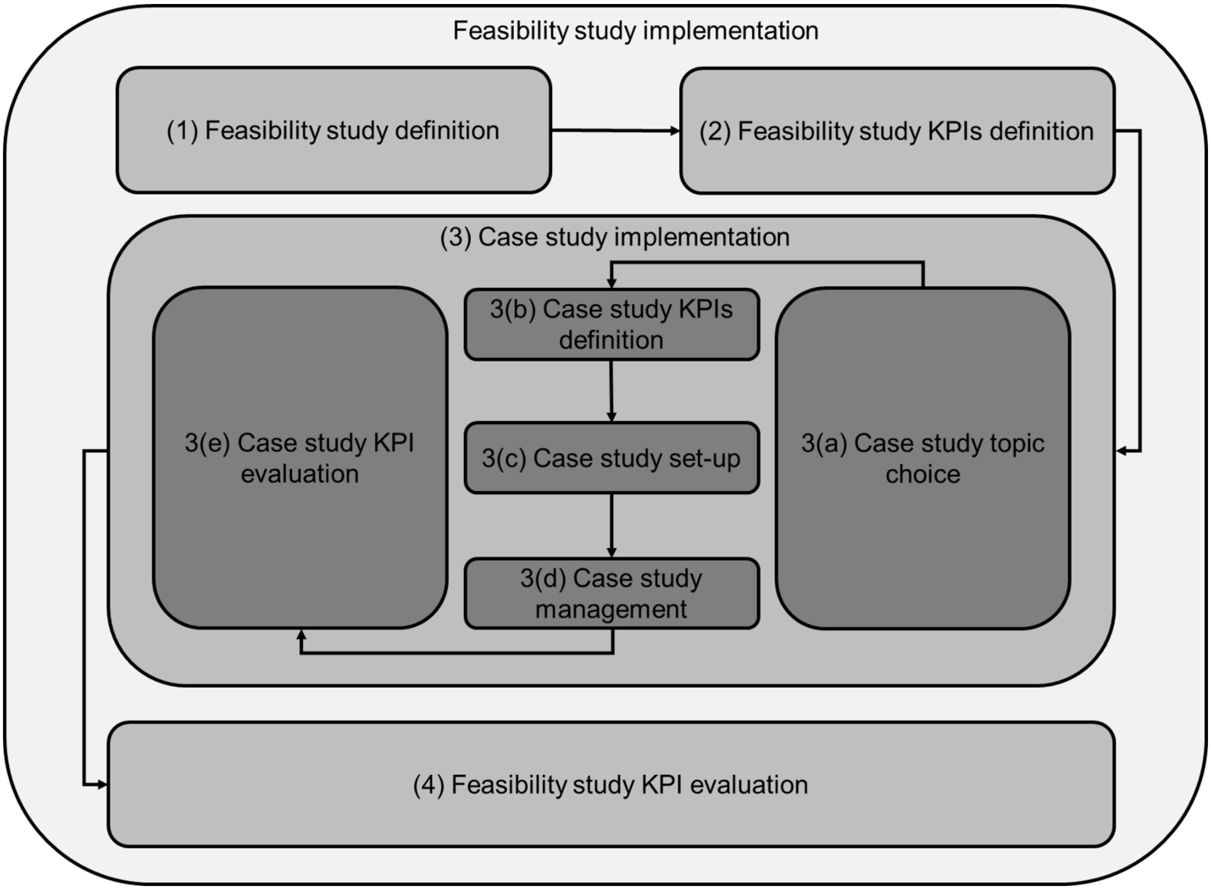

Figure 3. The feasibility study method used in this work.

3.1 Step 1: Feasibility study definition

The goal of the feasibility study was defined to be to test the general feasibility of the WeDoWind open innovation ecosystem for fostering open science and open innovation in wind energy. It was decided to do this with the help of a case study inside the WeDoWind Collaborative Problem-Solving Community, because this is currently the most active community. Future feasibility studies will focus on the other communities.

3.2 Step 2: Feasibility study KPIs definition

The KPIs for evaluating the feasibility of the WeDoWind open innovation ecosystem for fostering open science and open innovation in wind energy were chosen based on the TELOS aspects Technical, Economic, Legal, Operational and Scheduling (Bause et al., 2014), adapted for our purpose as follows (TELOS aspect marked with the corresponding letter in brackets):

- KPI Network Maturity (O): How well-developed, connected and functional the ecosystems relationships are, measured through the number and type of interactions between participants.

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- KPI Community Traction (O): How engaged the community is, measured by the number of participants and partner organisations over time, and the number of participants per activity.
- KPI Usability of Results (T): How valuable and applicable the outputs are for users, measured by the number of usable codes, information models and guidelines developed, and their adoption.
- KPI Technical Maturity (T): How advanced, stable and scalable the technical infrastructure is, measured by the platform's technical performance and capacity to grow.
- KPI Market Demand (E): The level of interest, need and willingness to engage, measured by the percentage of users who rate WeDoWind as unique, the number of organisations participating in challenges and working groups, and the number of stakeholders committing resources such as money and time.
- KPI Competitive Landscape (E): How WeDoWind compares to other open innovation platforms or challenge providers, measured by the number or competitors and the distinctness of WeDoWind's offer.
- KPI Financial Sustainability (E): How well operational costs can be covered in the long-term, measured through the funding obtained so far.
- KPI Partnership & Governance (L): The quality of the partnerships and decision structures, measured by the breadth and balance of stakeholders and the formal structured supporting collaboration.
- KPI Regulatory / IP compliance (L): How well the ecosystem adheres to relevant laws and standards governing data protection and IP, measured through the clarity and fairness of data protection and IP rules.
- KPI Scalability & Replication Potential (S): Capacity to expand operations and be reproduced in other sectors, measured by how clearly the processes are defined and how transferable they are.
- KPI Technology & Implementation Risks (T/O): The likelihood and impact of failures or delays in development, measured by considering which factors are relied upon for success.

It was decided to evaluate each aspect as "Low", "Low-Medium", "Medium", "Medium-High" and "High", based on a general assessment of the ecosystem, each decision accompanied by an explanation for the choice. To support the evaluation of these feasibility study KPIs, a case study was used as described in the next section.

3.3 Step 3: Case study implementation

Following the definition of the feasibility study and its KPIs, the case study was implemented as described in this section.

3.3.1 Step 3(a): Case study topic choice

A wind turbine structural health monitoring (SHM) challenge was chosen for the case study, due to the attractiveness of the topic and availability of relevant data. Current SHM research for wind energy is centred around fault detection using vibration data. At the sensor-level, fully unsupervised Long Short-Term Memory autoencoders trained only on healthy accelerometer streams have delivered sub-second anomaly scores for onshore wind turbines have achieved 98% recall on field data (Lee et al., 2024). Recently, a deep-boosted transfer learning strategy re-weighted source-domain samples during training, raising gearbox-fault recognition accuracy by about 10% compared with conventional Convolutional Neural Network baselines under variable loads (Jamil et al., 2022). Scaling from single machines to entire fleets, an unsupervised ensemble of isolation-forest and variational-autoencoder detectors performed fleet-based monitoring directly on vibration envelopes, flagging bearing damage up to three weeks earlier than existing SCADA[7] metrics (de Novaes Pires Leite et al., 2023). Other work coupled graph neural networks with sparse-filtering feature extraction to exploit the topological correlations of multi-sensor arrays, boosting gearbox-fault F1-scores above 95% on high frequency datasets (Wang and Loparo, 2023). For rotor blade health, a hybrid variational-autoencoder/neural Ordinary Differential Equations model tracked subtle shifts in modal signatures and correctly classified leading edge cracks in complex, turbulent inflow, demonstrating the promise of physics-aware deep generative models (Yang et al., 2024).

The research on this topic is active, and a lack of comparison between methods and results can be observed. Therefore, there is not a high level of understanding in the community about the advantages and disadvantages of different methods. A WeDoWind challenge aimed at comparing different SHM fault detection methods therefore has a high potential to be useful to the community.

3.3.2 Step 3(b): Case study KPIs definition

In order to support the evaluation the feasibility study's KPIs, the purpose of the case study was decided to be to test how well the WeDoWind open innovation ecosystem allows the results of different methods (or challenge solutions) to be compared. For this, the following case study KPIs were defined:

- KPI Evaluation Metrics: How well comparison metrics can be used to compare the performance of the different methods.
- KPI Advantages and Disadvantages: How well the solution templates provided in the challenge allow the advantages and disadvantages of different methods to be compared.
- KPI Evaluation Panel: How well the Evaluation Panel assessment can be used to compare different methods.
- KPI Participant Satisfaction: How satisfied the participants were with the challenge and how likely they are to take part in future challenges.

[7] Supervisory Control and Data Acquisition

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- KPI New Activity: The amount of new activity generated, such as platform posts, discussions, webinar recordings and events.

As for the feasibility study, it was decided to evaluate the KPIs as "Low", "Low-Medium", "Medium", "Medium-High" and "High", based on the case study results, each decision accompanied by an explanation for the choice.

3.3.3 Step 3(c): Case study set-up

The ASCE-EMI Structural Health Monitoring for Wind Energy Challenge was created in collaboration with the American Society of Civil Engineers Structural Health Monitoring & Control Committee and RTDT Laboratories AG, who provided measurement data on an operating wind turbine. The available dataset (Chatzi et al., 2023) provides comprehensive operational and structural measurements from the Aventa AV-7 wind turbine located in Taggenberg, near Winterthur, Switzerland. Commissioned in December 2002, this 7 kW turbine features a 12.8 m rotor diameter and an 18 m hub height, operating with variable speed and variable pitch control systems. To assess the turbine's structural integrity as it approaches the end of its design life, ETH Zurich initiated a measurement campaign in 2020, which remains ongoing. Instrumentation includes 11 accelerometers along the tower and nacelle, two full-bridge strain gauges on the tower, and sensors for temperature and humidity. Data acquisition rates are 200 Hz for acceleration and strain, 1 Hz for environmental parameters, and 10 Hz for SCADA signals such as wind speed, rotor RPM, power output, and turbine status. The dataset encompasses four operational scenarios: normal operation, aerodynamic imbalance, rotor icing, and pitch system failure. Accompanying materials include metadata in JSON and YAML formats, sensor specifications, example code in a Jupyter notebook, and media files illustrating turbine conditions. The challenge is described on the WeDoWind platform[8] as follows:

[8]https://community.wedowind.ch/spaces/17204906/content

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As wind turbines become larger and more difficult to monitor on-site, the need for remote SHM solutions is increasing. However, the wind energy industry has not yet concluded on a go-to practice for SHM of wind energy structures, with research efforts on efficient methods and tools still underway. In this challenge, the aim is to offer a platform for the comparison of existing methods and development of new SHM schemes for wind energy together! Based on a open dataset, we here focus on unsupervised methods for classifying faults. The goal of this challenge is to detect three fault events with the highest possible accuracy. The fault events are:

- *Pitch drive flexible coupling failure (FC)*
- *Aerodynamic imbalance (AI)*
- *Rotor icing (RI)*

For each fault event, the method applied should be clearly outlined, with an explicit description of the datasets used for training, testing and validation. Additionally, the results should be appropriately quantified via use of a confusion matrix, and a tabularised reporting of the accuracy, precision, recall and F-score metrics.

The participants were supplied with a report template, a repository on GitHub for uploading their code[9] and were required to fill out a feedback form. An Evaluation Panel consisting of five experts from the field[10] evaluated the results according to the following criteria:

- The reporting of the employed method and the novelty of the adopted approach.
- The ranking of the delivered accuracy, precision, recall and F-scores for the schemes that are tried out.

The submissions were assigned overall scores, and first prize, second prize and third prize were awarded, as well as participation certificates for all participants.

3.3.4 Step 3(d): Case study management

The challenge was launched via a webinar on June 21st, 2024, and finished on February 3rd, 2025. The challenge description was published on the WeDoWind platform, where registration and participation instructions were provided. The platform provided a discussion forum for questions, meeting invites for monthly webinars for asking questions and discussing solutions, access to webinar recordings, and links to the data and solution ideas. The results were regularly communicated on WeDoWind and LinkedIn. The results were submitted using a report template, and presented at the final presentation.

[9] https://github.com/RTDT-LABORATORIES/wedowind-challenge-ASCE-EMI

[10] Prof. Eleni Chatzi, ETH Zurich, Switzerland; Dr. Imad Abdallah, RTDT Laboratories, Switzerland; Prof. Jian Li, University of Kansas; Prof. Fernando Moreu, University of New Mexico, USA; Prof. Susu Xu, John Hopkins University, USA

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3.3.5 Step 3(e): Case study KPI evaluation

In order to test how well comparison metrics could be used to compare the performance of the different methods (KPI Evaluation Metrics) and how well the challenge allowed the advantages and disadvantages of different methods to be compared (KPI Advantages and Disadvantages), the final reports were used by the challenge organisers to create a table summarising the type of method, a short description of the method, and the accuracy, precision, recall and F-scores (where available) for each solution. In order to test how well the Evaluation Panel assessment could be used to compare the results (KPI Evaluation Panel), a template for the Evaluation Panel was created, and the solutions were discussed and then ranked at an Evaluation Panel meeting. This was used to create a short WeDoWind post announcing the results and the reasons for the choices. In order to test how satisfied the participants were with the challenge and how likely they are to take part in future challenges (KPI Participant Satisfaction), a participant survey was carried out. In order to test the amount of new activity generated, such as platform posts, discussions, webinar recordings and events (KPI New Activity), the platform analytics were analysed using an in-built analytics tool. For each case study KPI, an assessment of "Low", "Low-Medium", "Medium", "Medium-High" and "High" was then carried out, and each decision was accompanied by an explanation for the choice.

3.4 Step 4: Feasibility study KPIs evaluation

For the evaluation of the feasibility study KPIs, a qualitative analysis of the status of the ecosystem was carried out, evaluating each KPI as "Low", "Low-Medium", "Medium", "Medium-High" and "High". The evaluation of the case study KPIs from Step (3) helped with this assessment; however, the feasibility study was more generally applied to the entire ecosystem.

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4 Results

In this section, the results of the case study are first presented, followed by the results of the feasibility study.

4.1 Case study

The final reports of the five solutions that were submitted for the challenge can be found on the WeDoWind platform[11]. Evaluations of the case study KPIs are presented below.

4.1.1 KPI Comparison Metrics

Table 1 shows a summary of the type of method, a short description of the method, and the accuracy, precision, recall and F-scores (where available) for each solution, including the direct link to the relevant report and the GitHub code.

The **PyMLDA Open-Code method (PyMLDA)** is an unsupervised multi-classification clustering including data processing, feature selection, pattern recognition, clustering, classification techniques, and evaluation of ML models. The monitoring process begins with data acquisition from the wind turbine, followed by data pre-processing that involves spectral analysis and sensor verification. The next step is feature selection, which reduces the spectral signal and extracts information into a refined set of statistical and spectral analysis. A supervised sensitivity analysis then identifies the most sensitive features, which are normalised using a relative change damage index (Rc_f). These normalised features are clustered using the unsupervised k-means algorithm, with the elbow method determining the optimal number of clusters. The resulting clustered dataset is split into training/validation and testing batches. Six supervised machine learning models (SVM, KNN, Naive Bayes (NB), Random Forest (RF), Decision Tree (DT), XGBoost) are trained and evaluated using Scikit-learn, with performance assessed through metrics such as Accuracy, Precision, Recall, F1-Score, and confusion matrices. A five-fold cross-validation is applied to enhance generalisation and prevent overfitting. The code also indicates the best ML models based on their evaluation metrics. Binary and multiple classifications can be performed.

The **Health Index Monitoring with Variational Autoencoders (HIM-VAE)** method is a Wind turbine fault detection framework that integrates multi-domain feature extraction with a variational autoencoder (VAE) architecture. First, it extracts comprehensive feature sets from raw vibration signals, capturing both time-domain characteristics and frequency-domain properties. Specifically, 20 distinct features are extracted: 13 time-domain features (including standard deviation, root mean square, maximum/minimum values, peak-to-peak value, skewness, kurtosis, waveform factor, peak factor, impulse factor, absolute mean value, crest factor, and clearance factor) and seven frequency-domain features (spectral mean, variance, standard deviation, entropy, energy, skewness, and kurtosis). These features create a robust representation of normal turbine behaviour. The VAE architecture forms the core of the solution. The encoder transforms the extracted feature set into a regularised latent space, characterised by mean (μ) and standard deviation (σ) vectors, constraining them to approximate a standard multivariate normal distribution $\mathcal{N}(0, I)$. A latent vector is sampled from this distribution and passed to the decoder, which reconstructs the original features. This process is guided by a loss function combining reconstruction error (RE) and Kullback-Leibler

[11] https://community.wedowind.ch/spaces/17204906/content

divergence, enabling the model to learn meaningful representations of normal operational states. For anomaly detection, the framework employs exponentially weighted moving average (EWMA) to process reconstruction errors, which significantly enhances detection capabilities by reducing random fluctuations while preserving meaningful deviations. The solution implements a systematic two-phase approach to health monitoring. During the training phase, historical normal operation data undergoes pre-processing to remove outliers and trends, ensuring an accurate baseline representation. The data is then divided into training and validation samples. Training samples are used to extract features and train the model, while validation samples are utilised for setting threshold limits to decide when a sample is diagnosed as faulty. The monitoring phase applies this trained model to real-time vibration data, where signals exceeding the established EWMA threshold are classified as anomalous.

The **Unsupervised Event Classification using K-Means Clustering (UEC-K-Means)** method is an unsupervised event classification workflow using K-Means clustering to analyse time-series data representing normal operations and the three failure scenarios. An unsupervised event classification workflow was applied using K-Means clustering to analyse time-series data representing normal operations and the three failure scenarios, pitch drive failure, aerodynamic imbalance, and an icing event. The objective is to classify these events accurately to support early failure detection and predictive maintenance. The workflow consists of (1) data pre-processing, which involved collecting raw time-series data, with each 10-minute file corresponding to a clearly labelled event — either normal operation or one of three failure modes, merging these labelled instancesinto a unified dataset to support clustering-based model training, (2) K-means clustering, involving partitioning the feature space into four clusters, assigned each cluster with the event label that appears most frequently inside it, ensuring a unique mapping between events and clusters, and (3) testing and classification, assigning each data point for each new test file (i.e. a 10-minute data segment) to a cluster, and selecting the cluster containing the majority of these points as the predicted event type. Model performance is confirmed by comparing each source file's assigned cluster to its actual label, validating clustering accuracy.

The **unsupervised damage detection using a feature selection framework (LLC)** applies the unsupervised feature selection method Local Learning-Based Clustering, training the model using healthy data under normal operating conditions. The framework begins with data pre-processing to ensure data quality by removing interruptions and inconsistencies. Subsequently, time domain features are extracted for detecting icing events, and aerodynamic imbalance, while additional frequency domain features are extracted for pitch drive failure. To enhance model efficiency, feature selection is conducted to reduce dimensionality and eliminate redundancy. In this study, an unsupervised feature selection method, Local Learning-Based Clustering (LLC) was utilised. For this, time domain features such as maximum, minimum, mean, standard deviation and skewness were extracted from each record. This process resulted in a total of 35 features, calculated as the number of features per sensor multiplied by the number of sensors. Additionally, different anomaly detection algorithms were considered for various damage events. For example, the isolation forest algorithm was utilised (LLC-IF) for detecting the icing and aerodynamic imbalance events, while M-Cluster based on Density based spatial clustering of applications with noise (DBSCAN) was employed for detecting pitch drive failure (LLC-DBSCAN). For anomaly detection, the models were trained using healthy data obtained under normal operating conditions. Once the model achieved satisfactory training performance, it was employed to identify anomalies indicative of fault events.

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The **Combined ML methods (Combi)** is a multi-faceted methodology that integrates unsupervised learning methods—PELT Algorithm, Isolation Forest, and Rolling Variance with T-test—for anomaly detection, alongside a supervised classification framework comprising Random Forest, XGBoost, CatBoost, and Logistic Regression.

It can be seen in Table 1 that the comparison metrics (accuracy, precision, recall and F-scores) could be used to some extent to compare the performance of the different methods. The fact that some reports did not include these metrics specifically, or they were given for multiple different cases, made it more difficult to make a direct comparison. This KPI therefore receives a rating of "Low-Medium".

4.1.2 KPI Advantages and Disadvantages

The next table (Table 2) shows that the solution templates allowed the advantages and disadvantages of different challenge solutions to be compared. The **Combined ML methods (Combi)** is not included due to the lack of comparison metric results provided in the final report. It can be seen that the **PyMLDA method** successfully performed both binary and multiclass classification of operational failures, achieving accuracy rates of 99% to 100%. By integrating a multiphysics dataset, combining signals from multiple sensors and SCADA data, the approach enables the incorporation of environmental conditions into the learning and fault classification process. However, the method still relies on feature extraction based on mathematical formulations and signal condensation, which may generalise the information and limit specificity. Therefore, supervised analysis remains essential to ensure accurate interpretation of the dataset. The **HIM-VAE method** achieved 100% detection accuracy across all fault types, demonstrating the effectiveness for anomaly detection in SHM. However, this approach required careful outlier removal and high-quality training data, showing high sensitivity to data quality during pre-processing, which may limit its robustness in operational environments where data inconsistencies are common. The **UEC-K-Means method** effectively classifies multiple fault types simultaneously, achieving an accuracy of 77.3%. This capability supports faster and more efficient decision-making. However, when trained on smaller datasets, the accuracy tends to decrease due to increased overlap among fault patterns, which makes them more difficult to distinguish. The **LLC method** achieved satisfactory damage detection accuracy (more than 97%) across all fault types; utilising the most damage sensitive of the employed statistical and time-domain features. This was performed in an unsupervised manner. However, the proposed approach requires a complex feature extraction and selection process in acquiring the most damage sensitive features.

This type of comparison can not only help researchers understand how different fault detection methods work and behave in relation to each other, it can also help wind farm owner/operators with decision-making. Such a comparison reveals which methods are most accurate, which can run without labelled data, and which demands heavy feature engineering, enabling engineers to select the right tool without exhaustive trial-and-error. Trade-offs that might otherwise stay hidden, such as a model's sensitivity to noisy SCADA data or its computational overhead, emerge early, reducing costly surprises during deployment. This may feed directly into an optimised maintenance strategies. For example, if engineers know that **PyMLDA** already accounts for environmental effects or that **UEC-K-Means** is less accurate with sparse data, they can design monitoring schedules, data quality checks, and sensor investments more efficiently and accurately. As well as this, such a comparison fosters a benchmark culture: as new data arrives, teams can revisit and upgrade their analytics continuously. This KPI therefore receives a rating of "High".

4.1.3 KPI Evaluation Panel Assessment

The WeDoWind challenge Evaluation Panel members evaluated the results as follows:

- The **HIM-VAE method** was judged to have the highest impact for this application, due to the novel and relevant hybrid methodology, the resulting accuracy scores, as well as the high quality of the paper and presentation.
- The **PyMLDA** method was judged to have the second highest impact for this application, due to the novel and relevant hybrid methodology, the resulting accuracy scores, as well as the high quality of the paper and presentation. However, the lack of feature selection using SCADA data means that the transferability and applicability to unseen cases may be lower than some of the other methods.
- The **UEC-K-Means** method was judged to have the third highest impact for this application, and the Evaluation Panel appreciated the attempt to use a multiclass unsupervised approach, which could be very relevant for this application. However, the resulting scores were lower than some of the other semi-supervised methods submitted.
- The **LLC** method was judged to have a lower impact for this application than the others. While the accuracy scores were high, events cannot be predicted unless the event type is known in advance.
- The **Combi method** was judged to have a lower impact for this application than the others. The presentation of the methods and results made it difficult to assess its quality.

The Evaluation Panel was able to successfully rate and compare the different solutions. This KPI therefore receives a rating of "High".

4.1.4 KPI Participant Satisfaction

Following the completion of the challenge, the five participating teams filled out a survey designed to test how satisfied the participants were with the challenge and how likely they are to take part in future challenges. In order to compare the results with previous challenges (Barber et al., 2022, 2023b; Barber and Ding, 2024; Barber et al., 2024), the same questions were asked. The results of the quantitative questions are shown in Fig. 4, which were answered on a scale of 1-5, where 1 meant "strongly disagree" and 5 meant "strongly agree". In the figure, the questions are shown on the left and the answers grouped into percentage of answers in the "Agree", "Neutral" and "Disagree" categories, whereby "Agree" includes scores of 4 and 5, and "Disagree" contains scores of 1 and 2.

Although there were only five respondents in this survey, some general conclusions can be drawn. For example, it can be seen that the general benefits are rated highly, in particular the creation of new insights and ideas, understanding the challenges of using real data, the opportunity to compare work with others. The creation of new contacts and increased visibility scored

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slightly lower than the other benefits, aligning with the results of previous surveys. These benefits probably require a critical mass of users to be built up, which is currently the main focus of activities within the WeDoWind open innovation ecosystem.

The data quantity and documentation was also rated highly, with its quality rated slightly lower. Additional questions (not shown here) focused on data preparation revealed that four out of five participants used the structured metadata that was provided along with data in this challenge, and they all found that it saved time in the data preparation process. The same four participants also used the wind turbine metadata in .JSON format, three of them finding it easy to use and understand. Only three of them used the sensor metadata in .JSON format, all of them finding it easy to use and understand. The same four participants found the provided python code snipped for reading hdf5 files useful, and only three of them used the code inside the notebook to query the SCADA system codes. Suggested improvements for describing the data included providing clear guidelines on how the data was collected and correcting an error in the SCADA data time frequency (which needs to be looked into more to understand exactly what is meant).

The participants were very satisfied by the support provided by the challenge providers and platform operators, and fairly satisfied with the usefulness and ease of use of the new platform. Two users gave rather negative feedback, and should be further interviewed on the specifics. As for the previous challenges, the participants found the regular email reminders and updates motivating, and supported the formal evaluation method defined by the challenge providers at the beginning.

Finally, the potential of WeDoWind to help the wind energy sector benchmark and evaluate ML methods for various applications, and to provide a central knowledge hub for wind energy in the future was rated very highly, with all of the participants intending to take part in a WeDoWind challenge in the future.

In comparison to the previous challenges, Fig. 5 shows that the overall scores have steadily improved over time. These scores were calculated by averaging the total score for each question over all the questions, assuming each question has equal importance, for each challenge. This KPI therefore receives a rating of "Medium".

4.1.5 KPI New Activity

The new activity related to the case study was analysed using an in-built analytics tool. The challenge generated the following new activity:

- One new dataset made available to the community
- 14 new technical and administrative discussions on the platform
- Five webinar recordings
- Three public events (launch webinar, interim presentation, final presentation)
- Since November 2024, four new LinkedIn posts, three comments, 14 reposts and typically 1’000 impressions per post
- Ca. 200 new WeDoWind members during the challenge duration

It can be seen that the challenge generated some new activity; however, work is still required to multiply this and make full use of the network. This KPI therefore receives a rating of "Low-Medium".

Solution	Description	Contributor	Type	Performance
PyMLDA Open-Code method (PyMLDA) [12, 13]	Unsupervised multi-classification clustering including data processing, feature selection, pattern recognition, clustering, classification techniques, and evaluation of ML models	U. Brasilia	Hybrid	Accuracy = 99.49%; Precision = 99.52%; Recall = 99.56%; F1-Score = 99.54%
Health Index Monitoring with Variational Autoencoders (HIM-VAE)[14, 15]	Wind turbine fault detection framework that integrates multi-domain feature extraction with a variational autoencoder (VAE) architecture	U. Catalunya	USup.	100% for all metrics
Unsupervised Event Classification using K-Means Clustering (UEC-K-Means)[16, 17]	Unsupervised event classification workflow using K-Means clustering to analyse time-series data representing normal operations and the three failure scenarios	Texas A&M U.	USup.	Accuracy = 77.3%
Unsupervised damage detection using a feature selection framework (LLC)[18,19]	The unsupervised feature selection method, Local Learning-Based Clustering is applied, training the model using healthy data under normal operating conditions	UC Dublin	USup.	Rotor icing: 100% for all measures; For AI: Accuracy = 97.96%; Precision = 91.26%; Recall = 94.89%; F1-Score = 93.04; For FC: Accuracy = 99.88%; Precision = 99.83%; Recall = 100%; F1-Score = 99.91%
Combined ML methods (Combi)[20, 21]	A multi-faceted methodology that integrates unsupervised learning methods—PELT Algorithm, Isolation Forest, and Rolling Variance with T-test—for anomaly detection, alongside a supervised classification framework comprising Random Forest, XGBoost, CatBoost, and Logistic Regression	U. Deggendorf	Sup.	Results not quantified

Table 1. Summary of the solutions examined in this work, where Sup. means supervised and USup. means unsupervised.

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Method	Strengths	Weaknesses
PyMLDA	99–100% accuracy; integrates multisensor and SCADA data	Feature-engineering heavy; requires supervision
HIM-VAE	100% detection; strong anomaly detection	Sensitive to outliers and data quality
UEC-K-Means	Multi-fault classification; 77.3% accuracy	Higher accuracy achieved with larger training datasets
LLC	Unsupervised; >97% damage detection	Complex feature extraction

Table 2. Comparison of the strengths and weaknesses of the four methods with quantified results analysed in this work.

[12]https://github.com/mromarcela/wedowind-challenge-ASCE-EMI
[13]https://community.wedowind.ch/posts/the-rtdt-space-solution-failure-classification-in-the-aventa-wind-turbine-during-operation-using-pymlda-open-code-id4
[14]https://github.com/shun-wang1/wedowind-challenge-ASCE-EMI
[15]https://community.wedowind.ch/posts/the-rtdt-space-solution-fault-detection-in-wind-turbines-using-health-index-monitoring-with-variational-autoencoders-id8
[16]https://github.com/YaoTengHu/wedowind-challenge-ASCE-EMI.git
[17]https://community.wedowind.ch/posts/the-rtdt-space-solution-unsupervised-clustering-for-wind-turbine-fault-classification-aerodynamic-imbalance-icing-and-pitch-c id-9
[18]https://community.wedowind.ch/posts/the-rtdt-space-interim-solution-id6_ver03_an-unsupervised-damage-detection-framework-for-an-operating-wind-turbine
[19]https://github.com/tteeoo26/An-unsupervised-damage-detection-framework-for-an-operating-wind-turbine-ID_6-/tree/main
[20]https://github.com/Anmolsharma95/wedowind-challenge-ASCE-EMI
[21]https://community.wedowind.ch/posts/the-rtdt-space-solution-failure-analysis-investigation-of-wind-turbine-components-using-machine-learning-and-deep-learning- 01_02

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	ASCE		
Percentage of answers	**"Agree"**	**"Neutral"**	**"Disagree"**
General benefits			
Participation in this challenge gave me some new insights or ideas I can use for my research	100%	0%	0%
Participation in this challenge resulted in some useful new contacts	40%	60%	0%
Participation in this challenge increased my visibility in the wind energy sector	40%	40%	20%
Participation in this challenge helped me understand the challenges of using real data from the industry	100%	0%	0%
Participation in this challenge helped me compare my work with others and evaluate its success	80%	20%	0%
The challenge topic was realistic and interesting	100%	0%	0%
The data and the challenge			
The provided data was of sufficient QUALITY for solving the challenge	60%	40%	0%
The provided data was of sufficient QUANTITY for solving the challenge	100%	0%	0%
The provided data was sufficiently documented and labelled	80%	20%	0%
Support			
The challenge providers were active and supportive during the process	100%	0%	0%
The WeDoWind operators were active and supportive during the process	100%	0%	0%
The process			
The Relight platform was useful for summarising and centralising the knowledge relevant for the challenge	80%	0%	20%
The Mighty Networks platform was useful for summarising and centralising the knowledge relevant for the challenge	40%	60%	0%
The webinars were a useful way of sharing ideas	100%	0%	0%
The Relight platform was easy to use	40%	20%	40%
The Mighty Networks platform was easy to use	60%	0%	40%
The tech support of the Relight platform was sufficient	60%	20%	20%
The tech support of the Mighty Networks platform was sufficient	80%	0%	20%
The regular email updates were motivating	100%	0%	0%
Evaluation			
The existence of a formal evaluation method defined by the challenge providers at the beginning was positive	100%	0%	0%
Future potential			
WeDoWind could help the wind energy sector benchmark and evaluate ML methods for various applications in the future	80%	20%	0%
WeDoWind could provide a central knowledge hub for wind energy in the future	100%	0%	0%
I intend to take part in a WeDoWind challenge in the future	100%	0%	0%
I would like future WeDoWind challenges to include more collaboration components	100%	0%	0%

Figure 4. Results of the quantitative part of the participants' survey.

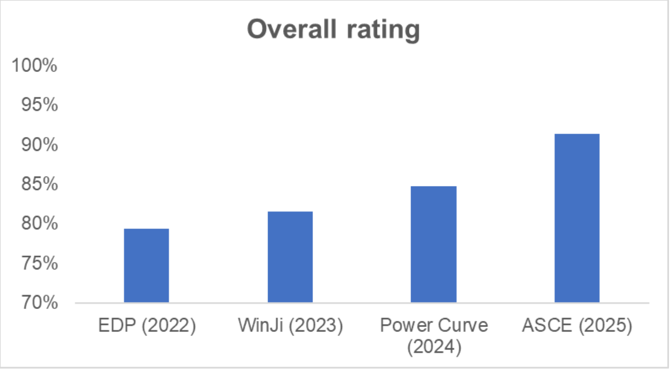

Figure 5. Comparison of the overall scores from the participants' survey between this challenge and previous challenges.

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4.1.6 Overall KPI evaluation

A summary of the case study KPI scores assigned in the previous sections is shown in Table 3. The ability of the WeDoWind open innovation ecosystem in allowing the results of different methods (or challenge solutions) to be compared for this case study was therefore assessed as "Medium" overall.

Case study KPI	Rating	Reason
KPI Evaluation Metrics	Low-Medium	A comparison could be made, but the fact that some reports did not include these metrics specifically, or they were given for multiple different cases, made it more difficult to make a direct comparison
KPI Advantages and Disadvantages	High	A detailed comparison of the advantages and disadvantages of the submitted solutions could be carried out
KPI Evaluation Panel	High	The Evaluation Panel was able to successfully rate and compare the different solutions
KPI Participant Satisfaction	Medium	The overall scores have steadily improved over time
KPI New Activity	Low-Medium	The challenge generated some new activity; however, work is still required to multiply this and make full use of the network

Table 3. Summary of the evaluation of the case study KPIs.

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4.2 Feasibility study

The results of a feasibility study of the WeDoWind open innovation ecosystem for fostering open science and open innovation in wind energy are shown in Fig. 4, using the evaluation of the case study KPIs to support the decisions.

The KPI Network Maturity was measured through the number and type of interactions between participants. For the case study, one new dataset was made available, five solutions were submitted, and the platform was used for discussions (14 new technical and administrative discussions were generated), webinars and events (five webinar recordings were uploaded and three public events were held). Since November 2024, four new LinkedIn posts, three comments, 14 reposts and typically 1'000 impressions per post were reached. The participants responded positively to the challenge. In the overall ecosystem, there are currently 419 members (as of 22.10.2025), with 20% to 60% of these members actively contributing to discussions or working groups (varying with month, directly relating to challenge events or deadlines). Since January 2025, 36 new LinkedIn posts were created related to WeDoWind, generating over 25'000 new impressions, almost 500 reactions, eight comments and 51 reposts. While this interaction is positive, the number and type of active contribution can be improved upon. This KPI was therefore rated as "Medium".

The KPI Community Traction was measured by the number of participants and partner organisations over time, and the number of participants per activity. For the case study, the development of the number of participants and partner organisations over time could not be measured. However, in the overall ecosystem, a steady increase in participants over time can be seen. The number of new members per month varied from 77 in January to 157 in May, with a general upward trend. As well as this, the number of partner organisations running challenges or working groups has steadily increaased over time. In January, the ecosystem included challenges run by EDP (the EDP Challenges space), WinJi (the WinJi Challenges space), Nuveen Infrastructure Clean Energy (the Open Data Exploration space), Georgia University of Technology (the Data Science for Wind Energy space), RTDT Laboratories AG (the RTDT space) and Chalmers Institue of Technoogy (the EAWE Test Turbines Committee space). As of October 2025, we have additionally partnered with RES (in the Hill of Towie Data space), Fraunhofer IEE (in the EnergyFaultDetector space), IEA Wind Task 43 (the Wind Energy Domain Ontology, Operations Ontology, Digital Twins Taxonomy and Data User groups), TIM-Wind, the Research Data Alliance (RDA Wind Energy Community Standards Working Group), Alisios Corporation (Data Engineering in Wind Energy space), Octue (for the Schema Publishing Portal), HES-SO (for the Ontology Publishing Portal) and the Swiss Data Science Center (for the Open Data Portal). While this community traction is encouraging, further interaction is required in order to reach the critical number required to benefit from the networking effect. This KPI was therefore rated as "Medium".

The KPI Usability of Results was measured by the number of usable codes, information models and guidelines developed, and their adoption. For the case study, five new codes were uploaded to the GitHub repository. In the overall ecosystem, a total of 22 codes have been uploaded to GitHub (five from this case study, six from the EDP Wind Turbine Failure Detection Challenge (Barber et al., 2022), six from the WinJi Gearbox Failure Detection Challenge (Barber et al., 2023b), five from the Power Curve Modelling Benchmarking Challenge (Barber and Ding, 2024)), and 22 codes have been made available

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on Kaggle (12 from the Predict the Wind Speed Challenge[22] and 10 from the running Hill of Towie Wind Turbine Power Prediction Challenge[23]). As well as this, 25 new ontologies have been uploaded to the TechnoPortal[24], and fours guidelines are under development in the Information Modelling Community and the Open Data and Code Community. This is a very encouraging result; however, the adoption stage has not started (or cannot be measured). For this reason, we are currently testing the use of a data science platform such as Renku to make the submitted codes more interoperable and reusable. This KPI was therefore rated as "Medium".

The KPI Technical Maturity was measured by the platform's technical performance and capacity to grow. For the case study, the phase 1 platform proved difficult for users to use, which was one of the reasons for switching to the new phase 2 platform. The new platform worked well for running the case study challenge, with positive feedback from the participants. In the overall ecosystem, the platform performed technically very well so far, due to the high maturity of the underlying Mighty Networks platform. As well as this, the TechnoPortal ontology publishing portal has so far worked well for publishing and viewing ontologies in the Information Modelling Community. However, the Open Data and Open Code Portals do not yet exist, and the data science platform Renku is still being tested, so further development is required. This KPI was therefore rated as "Medium".

The KPI Market Demand was measured by the percentage of users who rate WeDoWind as unique, the number of organisations participating in challenges and working groups, and the number of stakeholders committing resources such as money and time. For the case study, the five participants all rated WeDoWind as unique. Five different organisations (all from academia) submitted solutions, one organisation provided the data and the challenge topics, and a further 50 organisations (from industry and academia) joined the space as observers. In the overall ecosystem, we observe a general strong overall market demand, with stakeholders across the industry reporting the need for improving data sharing and common data standards (Clifton et al., 2023; Barber et al., 2023c), All the participant surveys run so far (run with a total of 23 people) rated WeDoWind as unique. Over all the challenges, we estimate contributions of a total of 50 people and organisations (the challenges related to the participant surveys plus five additional challenges without a participant survey). In the rest of the community, there are approximately five people working actively inside ten different working groups, making a total of 50 more active participants. This KPI was therefore rated as "Medium-High".

The KPI Competitive Landscape was measured by the number or competitors and the distinctness of WeDoWind's offer. For the case study, the participants particularly rated the potential of WeDoWind to help the wind energy sector benchmark and evaluate ML methods for various applications, and to provide a central knowledge hub for wind energy in the future very highly. In the overall ecosystem, the distinctiveness lies in the connection of the different communities related to data sharing, and in its openness. However, the space is very crowded, and it may be challenging to find traction. This KPI was therefore rated as "Medium".

The KPI Financial Sustainability was measured through the funding obtained so far. For the case study, no direct funding was available. In the overall ecosystem, funding has been received for developing the TechnoPortal (Swiss Open Research Data

[22]https://www.kaggle.com/competitions/predict-the-wind-speed-at-a-wind-turbine/code
[23]https://www.kaggle.com/competitions/hill-of-towie-wind-turbine-power-prediction/code
[24]https://technoportal.hevs.ch/

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Grants (CHORD): Track A 3rd Call), for developing and testing a dedicated data science platform and an Open Knowledge Hub (SDSC National Call for Projects 2025), for improving open science practices within IEA Wind Tasks using WeDoWind (Swiss Open Research Data Grants (CHORD)), and for running WeDoWind challenges (the TWEED Horizon Europe MSCA Doctoral Network[25]). However, no sustainable long-term business model for operating WeDoWind has been implemented so far, so the financial sustainability is limited. This KPI was therefore rated as "Low-Medium".

The KPI Partnership & Governance was measured by the breadth and balance of stakeholders and the formal structured supporting collaboration. For the case study, this KPI is not relevant. In the overall ecosystem, a formal structure has already been developed for the organisation. WeDoWind operates as a Swiss non-profit organisation, lead by the Eastern Switzerland University of Applied Sciences, with an elected Board of Directors (consisting of eight members from academia and industry) and Advisory Board (seven members from academia and industry). It is strongly integrated into IEA Wind Task 43. This KPI was therefore rated as "High".

The KPI Regulatory / IP compliance was measured through the clarity and fairness of data protection and IP rules. For the case study, a "freedom to publish statement" ("I agree that the source code of my approach may be made publicly available and published in an open research journal") was included in the final report template. In the overall ecosystem, the whole focus is centred on open and FAIR data and code, sharing liability and easing adoption in regulated environments. As well as this, a Code of Conduct guides users to fulfill the following the three ideas of Respect, Empower and Include[26]. This KPI was therefore rated as "High".

The KPI Scalability & Replication Potential was measured by how clearly the processes are defined and how transferable they are. For the case study, this KPI is not applicable. In the overall ecosystem, replication is possible through the sector-agnostic WeDoData Blueprint, which is explicitly positioned for extension to other sectors. However, the concept for scaling the ecosystem is not yet entirely clear. This KPI was therefore rated as "Medium-High".

The KPI Technology & Implementation Risks was measured by considering which factors are relied upon for success. For both the case study and the overall ecosystem, success is extremely dependent upon the number of participants, and their engagement (implementation risk), as well as on the correct functioning of the platform (technology risk). We estimate the risk of not being able to attracting enough participants as quite high, and the risk of the digital platform not working correctly as quite low. This KPI was therefore rated as "Medium".

The **overall feasibility** was assessed to be "Medium", because the ecosystem demonstrates strong governance, regulatory compliance, and scalability potential, supported by a growing and engaged community. However, its long-term success will depend on improving financial sustainability and increasing active participation to fully leverage the network and ensure continued growth.

[25]https://www.tweedproject.eu/
[26]https://community.wedowind.ch/posts/about-wedowind-code-of-conduct

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Factor	Rating	Feasibility
KPI Network Maturity	Medium	Ecosystem shows solid engagement across datasets, discussions, events, and social media activity, but the proportion of actively contributing members and the depth of interactions indicate that network participation and collaboration could still be strengthened
KPI Community Traction	Medium	Ecosystem shows steady growth in participants and partner organisations, indicating positive momentum, but has not yet reached the critical mass of engagement needed to fully realise the networking effect
KPI Usability of Results	Medium	a Strong foundation of usable outputs such as codes, ontologies, and guidelines has been created, but their actual adoption and reuse have not yet been demonstrated or measured
KPI Technical Maturity	Medium	Core platforms are technically stable and well-performing, but key components such as the Open Data and Open Code Portals are still under development, indicating that full technical maturity has not yet been reached
KPI Market Demand	Medium-High	Surveys and participation data show strong recognition of WeDoWind's uniqueness and growing engagement from both academic and industry stakeholders, though broader and deeper resource commitments are still developing
KPI Competitive Landscape	Medium	WeDoWind offers a distinctive and well-recognised value proposition through its openness and community connectivity, but operates in a crowded space where gaining strong traction and visibility remains challenging
KPI Financial Sustainability	Low-Medium	Several short-term funding sources have supported specific developments and activities, but a stable long-term business model for sustaining WeDoWind's operations has not yet been established
KPI Partnerships & Governance	High	WeDoWind has an established formal governance structure with balanced representation from academia and industry, operates as a recognised non-profit organisation, and is well integrated into the international IEA Wind Task 43 network
KPI Regulatory / IP Compliance	High	WeDoWind has clear, fair, and transparent data protection and IP principles embedded in its open and FAIR data approach, supported by a Code of Conduct that promotes responsible and inclusive collaboration
KPI Scalability & Replication Potential	Medium-High	The WeDoData Blueprint provides a well-defined, sector-agnostic framework that enables replication beyond wind energy, even though the broader scaling concept for the ecosystem is still being refined
KPI Technology & Implementation Risks	Medium	The platform's technical reliability is strong, but the high dependency on sustained participant engagement poses a significant implementation risk to long-term success

Table 4. Summary of the feasibility study of the WeDoWind open innovation ecosystem.

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5 Conclusions

A two-phase Design Thinking approach was applied to transform WeDoWind from a platform for documenting and managing challenges to an open innovation ecosystem for fostering open science and open innovation in wind energy. The feasibility of WeDoWind was evaluated across eleven key performance indicators (KPIs) adapted from the TELOS framework with the support of a structural health monitoring case study. The results of the case study, the ASCE-EMI Structural Health Monitoring for Wind Energy Challenge, demonstrated that WeDoWind enables the comparison and benchmarking of different machine learning methods for fault detection, while providing a structured and transparent framework for collaboration and data sharing. The overall feasibility was rated as "Medium," due to the strong governance, clear regulation, and promising scalability potential. However, further progress is required to make it financially sustainable, to ensure adoption of the results in the sector, and to ensure community engagement to reach the critical mass necessary for self-sustaining growth. Future work will focus on extending the WeDoData Blueprint to other energy sectors, developing the Open Data and Open Code Portals, and establishing a long-term business model to ensure the continued operation and expansion of WeDoWind. These steps will be essential to strengthen its role as an open, FAIR, and collaborative ecosystem that accelerates innovation and digitalisation in wind energy.

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Code availability. The scripts developed in this work are all available on GitHub[27].

515 *Data availability.* The data used for the case study in this work is available in (Chatzi et al., 2023)

Author contributions. SB: project lead, challenge coordination, paper writing, construction of summary table, definition of conclusions; SW, FP, YV, MRM, ARSRdS, JdSC, XZ, YTH, AN, TV, MA, RG, AM: challenge solution providers, paper editing. ChatGPT o-3 was used to help create the summary of the results and conclusions.

Competing interests. At least one of the (co-)authors is a member of the editorial board of Wind Energy Science

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[27] https://github.com/RTDT-LABORATORIES/wedowind-challenge-ASCE-EMI

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