P L 4 N E T

Enabling Wind Energy Revolution

Monitor and improve the efficiency of production processes

The Challenge

Wind energy can play a critical role in the transition to renewable and green energy. Wind turbines are subjected to various environmental conditions, wear and tear, and mechanical stresses that can affect their efficiency and lead to unexpected failures and costly downtime. Implementing Industry 4.0 solutions can address this challenge by enabling efficiency maximization and predictive maintenance. The challenge is to develop a system that leverages IoT sensors, data analytics, augmented reality, and machine learning to predict when specific components of a wind turbine are likely to fail, allowing proactive maintenance and reducing operational costs.

Industry Sector:
Wind Energy

Challenge classification:
Real-time Performance and Process Monitoring; Maintenance; Operations Planning and Scheduling

Time for Project Completion:
12 months

Main Requirements

- Digital Twin Development: create highly detailed replicas of wind turbines, incorporating real-time data from sensors, maintenance history, and environmental conditions
- Predictive Maintenance: use AI and ML to predict potential maintenance needs, including components wear and potential failures

Other Requirements

- Augmented Reality for remote inspection and maintenance guidance
- Energy Yield Optimization for dynamically adjusting turbine operation parameters

Key Performance Indicators

N/A

Other informations
N/A

Research Phase

Taking into account the challenge description, its requirements and its information, elaborate at least 5 questions that can lead your research for a solution.

Research questions:

1. Which type of data do we need to collect and monitor?
2. Which existing product or system can be used to integrate a (possible) big variety of data type and sources?
3. How can we show the data and possible insights to final users?
4. Which technologies can be used to allow remote inspections?
5. How can we analyze the data to give insight about turbine statuses and to alert if something is wrong?

Given the questions and the main requirements of the challenge previously listed:

- *identify possible technologies using the Planet4 Taxonomy Explorer;*
- *identify and analyze the sources (papers, articles, etc.) of those technologies that best suit the challenge;*

Technologies identified in the taxonomy:

1. Time Series Databases
2. Microsoft PowerBI
3. Grafana
4. Python
5. Deep Neural Networks
6. Edge Computing
7. Industrial IoT gateways and Data Acquisition Devices
8. Virtual Reality

Sources of those technologies that best suit the challenge:

1. E. D. I. Consortium, “Remote measurements control | EDI - european data incubator.”
2. https://powerbi.microsoft.com/
3. https://grafana.com/
4. STMicroelectronics, “Predictive maintenance at LACROIX Electronics.”
5. S.Heo et al., “Data-Driven Hybrid Model for Forecasting Waste water Influent Loads Based on Multimodal and Ensemble Deep Learning.”
6. Libelium, “Smart Industry 4.0 technology - industrial internet of things (IIoT) libelium.”
7. https://zerynth.com/
8. M.Group, “5G technology: Enabling the IoT, AI and Industry 4.0 - research | merck global.”

In light of the discoveries made:

- *report the answers for the questions above;*
- *compare 2-3 of the more common solutions identified in the sources (how would they change the approach to the solution? What are the possible benefits/issues in such a use of these technologies?);*
- *draw initial conclusions on which path you want to take in proposing a solution.*

Answers:

1. In order to effectively address the requirements of our project, it is imperative that we gather data from a diverse array of sensors and cameras. This data amalgamation necessitates a database architecture that is not only versatile but also adept at handling temporal data. In this specific context, Time Series Databases have emerged as the prevailing choice, and they have consistently demonstrated their capacity to surmount the challenges associated with the management of temporal data.
2. Zerynth's hardware has showcased remarkable flexibility as data collection devices, excelling in the domain of data streaming. Beyond data collection, these devices offer the added advantage of enabling on-the-edge computation and data pre-processing. This multifaceted utility streamlines data processing and enhances the efficiency of our entire data acquisition system.
3. To visualize and analyze the data we collect, we can employ Grafana, a versatile platform that offers a plethora of visualization tools and customizable dashboards. These dashboards are instrumental in the presentation of real-time temporal data originating from the diverse array of sensors we employ. Furthermore, Grafana equips us with alert plotting functionalities, which are invaluable for real-time anomaly detection and response. Notably, Zerynth devices seamlessly integrate into this ecosystem, acting as inputs for generating Grafana dashboards through Zerynth's cloud infrastructure. This synergy between Zerynth and Grafana further augments our data visualization capabilities, facilitating efficient data-driven decision-making.
4. Virtual reality stands out as a transformative force in the realm of remote maintenance across various industrial equipment. By offering an immersive, three-dimensional visualization environment, VR has the capacity to revolutionize maintenance processes. This is particularly relevant in the context of wind turbines and other intricate machinery, where an immersive experience can uncover hidden intricacies that may remain concealed when employing conventional 2D interfaces. Moreover, the integration of VR with IoT sensors introduces a new dimension of real-time monitoring.
5. Deep Learning emerges as a powerful tool, particularly in the domain of predictive maintenance. The incredible results demonstrated by DL in various applications underscore its potential to enhance the reliability of maintenance operations. Furthermore, the advent of multimodal DL models enables the utilization and simultaneous processing of diverse data types. This fusion of knowledge gleaned from distinct sensors and cameras facilitates the understanding of equipment health and performance, contributing to more accurate predictive maintenance.

Comparison:

The solutions to the research questions for this challenge mainly adopt techniques and methods coming from the following subfields.

Data Collection Methods:

The data collection process can be solved mainly via IoT sensors data and data acquisition systems. The specific technology used for this process can vary, but usually there can be problems in different platforms communication and integration. The choice of Zerynth devices can solve this issue and its seamless integration with other adopted technologies can save a huge amount of work and time.

Data Analysis Techniques:

Regarding data analysis, the proposed solution suggests the use of Deep Learning. The field of data analysis received a lot of attention from the academic world and an enormous amount of techniques and algorithms have been proposed in the last decades. However, DL models seem the most flexible and allow users to handle different data sources. On the contrary, other AI algorithms are usually tailored for specific solutions and are capable of processing a single data type (like images, or tabular data). Deep learning, and specifically multimodal deep learning models, instead, can combine knowledge from different sources and provide (usually) better results. This feature can be a crucial one in this challenge, since the monitoring of surrounding environment and turbine statuses can possibly be carried out with cameras.

User-Centric Delivery of Insights:

As well as the previous ones, this field has been very well studied since the beginning of the digital era. Other than Virtual Reality, a variety of techniques can be used for delivering insights from collected data. Among them, most of them do not provide a full remote usability or can be too difficult to implement. For example, Augmented Reality and Mixed Reality allow for interaction between a final user and the surrounding environment. However, the first one requires physical access to the desidered environment and does not support fully remote usability, while the second one can be difficult to reproduce because a full physical simulation of the environment is needed. VR can be a suitable compromise between simulation and full remote usability.

Conclusions:

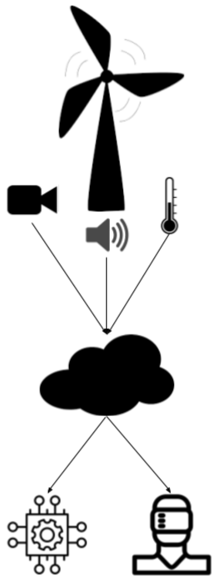
In conclusion, our proposed solution offers a robust, technologically advanced framework for addressing complex maintenance and data management challenges. It combines various cutting-edge technologies to optimize data collection, analysis, and predictive maintenance. The solution's versatility and efficiency are evident in its use of Time Series Databases, Zerynth hardware, Grafana for data visualization, virtual reality for immersive maintenance, and deep learning for predictive analysis. This integrated approach ensures efficient equipment monitoring, reduced downtime, cost savings, and enhanced safety. Virtual reality, in particular, stands out for its ability to provide immersive, 3D visualization, making it highly effective for scenarios that require a comprehensive understanding of complex machinery.

Proposed Solution

Making use of the technologies identified after the analysis of the sources, describe a possible solution to the challenge. Also, do not forget the constraints (time, number of devices to produce/connect, etc.): the solution must be applicable to the real context of the company that commissioned the challenge.

Solution Summary

Our solution adopts a robust infrastructure that harnesses the capabilities of Time Series Databases, Zerynth's versatile hardware, and the visualization power of Grafana. Time Series Databases seamlessly manage the temporal data required for monitoring equipment health and performance. Zerynth's hardware not only serves as a flexible data collection tool but also reduces downtime and maintenance expenses. Grafana complements this data-driven approach by offering real-time insights and alerting functionalities.
Regarding the predictive maintenance and immersive visualization part of the challenge, our solution employs virtual reality (VR) and deep learning (DL) as transformative tools. VR's immersive, three-dimensional visualization capability provides a comprehensive understanding of intricate machinery and is particularly valuable for maintenance and training. The integration of VR with IoT sensors enables real-time monitoring and proactive maintenance. Deep Learning, on the other hand, introduces a higher degree of accuracy and early anomaly detection in predictive maintenance scenarios. Multimodal DL models enhance these capabilities by aggregating insights from diverse data sources.



Solution Description

The first steps of the proposed solution are the infrastructure development and the connection with the

devices. A time series database must be built, and API connections must be supported, in order to guarantee the connection with the Zerynth devices and possibly smart cameras.
Zerynth devices must be programmed as well. Their firmware must be created in order to collect the data with given frequencies, pre-processed it on the edge, and send it to the database. At the same time, the front-end team should create real-time dashboards in Grafana, allowing users to have a first glance of the situation in the desired environment.
Once the infrastructure is set up and data starts to flow, more advanced data analysis and manipulation techniques must be developed. Incoming data can be used to train a multimodal DL model. Finally, IoT sensors and VR engine integration can be carried out, to enhance final users to easily navigate the digital twin of the desired wind turbine and its surrounding environment.

Implementation Plan

Describe the solution implementation plan considering among other things: gantt chart with milestones, high-level cost analysis, possible difficulties (at least 3 major issues or difficulties) and additional opportunities (at least 2 extra benefits).

	Time in Weeks								
	5	10	15	20	25	30	35	40	45
Database construction									
Hardware deployment									
Data collection and corrections									
DL model development									
VR system development									
Feedbacks and modifications									

The previous table shows the GANTT chart for the implementation of the proposed solution. The proposed tasks are the same described in the description of the solution, plus two troubleshooting phases. The first one can be performed during the data collection phase, in order to minimize the total completion time. The second one should be performed at the end of the development phase, in which final users suggestions and needs can be obtained and their requests can be met.

High level cost analysis:

Costs of the solution can be divided into equipment costs and human labor costs. The first one mainly affects the initial phase, when the hardware and cloud storage must be obtained, and the last one, for final users equipment. The total cost for these two steps could sum up to 10,000$.

Human labor for the development phases represents the biggest fraction of the total cost. This solution requires at least two backend software engineers, a mechanical engineer for the deployment of the hardware and a supervision for the VR development, a machine learning expert and a VR expert, and a project leader. The cost for these highly-skilled employees for the time needed sum up to 60,000$. In conclusion, a possible total cost for this solution can be 70,000$.

Possible Difficulties:

- Highly-skilled employees: all the proposed milestones require educated workers, with hard skills in Computer Science, Engineering, and Data Analysis. Finding these highly-specialized professional figures can be a very difficult task.
- Development bottlenecks: the more advanced features of the proposed solutions must be built upon a very efficient and reliable data acquisition system. Any problem and missed milestone of the initial phase will slow down the development of the most advanced ones.
- User Adoption: promoting the adoption of data-driven decision-making among users may encounter some reluctance. Addressing this hurdle necessitates the implementation of effective training and change management approaches, which can be particularly demanding in the industrial sector due to its unique intricacies.

Additional Benefits:

- Energy Efficiency: the solution will lead to reduced energy consumption, contributing to cost savings and environmental sustainability.
- Marketing Improvement: the huge hype in both renewable energy sources and machine learning, can severely boost the appeal of the company in the market.