Software Proposal Document for Fault Detection and Power Prediction of Wind Turbines

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Proposal Version	Date	Reason for Change
1.0	4-November-2021	Proposal first version's specifications are defined
1.1	7-November-2021	Document updated

Table 1: Document version history

GitHub: https://github.com/zeinadesouky/Fault-Detection-In-Wind-Turbines

Abstract

Institutions have been rapidly redirecting their investments away from fossil fuels, creating a favorable scenario for the generation of clean energy. The wind industry, especially, has seen an exponential increase in recent years. Early fault detection creates an alternative for operation and maintenance (O&M), helping forgo costs before they reach a catastrophic stage since preventive methods are used to stop malfunctions before their occurrence, improving turbine reliability. Wind power generation prediction allows for maximum utilization and better control of the wind farms. In this document, deep learning methods such as LTSM (Long short-term memory) is used on time series data produced from SCADA to reach the optimal results.

1 Introduction

1.1 Background

Energy is now a crucial part of living on Earth. Almost everything depends on the use of energy. For a long time, the main source of energy has been fossil fuels, which, however, comes with major drawbacks. The use of fossil fuels plays a major role in climate change and affects air pollution negatively, consequently, impacting humans and living creatures [10]. People tended to move to less harmful energy sources, and the wind was one of those.

The first sale of commercial wind turbines was finalized in 1927, to a group of US farmers for what was considered a fairly high price, but it was the 1970s oil crisis in the Middle East that pushed various governments to fund research into renewable energy as a means not only for energy security but also to battle air pollution and climate change[18].

Maintenance of wind turbines used to occur twice a year within 6 months of each other. A thorough inspection would occur upon the system, along with repairs and replacements according to the technician. This process was deemed time-consuming and costly and that led to the introduction of condition monitoring and later machine learning for fault detection.

1.2 Motivation

1.2.1 Academic

The use of renewable energy is now becoming the best alternative to reduce reliance on fossil fuels. As renewable energy proceeds in its rapid growth around the world, the need for prediction and forecasting tools increases as well. Machine learning provided a novel solution for this need, and as a result, renewable energy sources will become more reliable and affordable and increase in expansion and potential[19].

A major energy source is wind. While wind can be a solution to the major climate change resulting from the use of non-renewable energy, converting it to energy is a long process that includes major steps. Since wind turbines are the source of wind energy, they require maintenance as they are placed in remote locations, which subject them to failures, with harsh environmental conditions. Failures in wind turbines can be costly. A current solution that is now being implemented is to detect possible faults using condition monitoring. It, however, needs knowledgeable professionals to analyze the data and perform the work. A possible improvement to condition monitoring is using machine learning models to develop systems that would eliminate the hassle of finding professionals for doing the job.

1.2.2 Business

Renewable energy sources in 2013 accounted for an estimate of 19.1% of energy consumption. The Energy Roadmap aims that the energy supply specifically of wind to reach a number between 31.6% and 48.7% in 2050. This increase, however, will have a major impact on the O&M of the costs of wind turbines.[2] The figure below shows the increase in the global investments in wind power[3]. That being said, systems that could monitor and detect potential failures in wind turbines would benefit the world greatly by limiting the time of downtimes and thus minimizing loss of revenue[17].

1.3 Problem Statement

To avoid wind interference near cities, wind turbines are mostly located in secluded areas. Due to this allocation, the operation and maintenance costs tend to surge and the conditions of it (OM) become increasingly volatile due to unpredictable weather conditions. By predicting the faults in wind turbines before they occur and maintaining them accordingly and forecasting weather variables to predict wind power generation, the costs of maintenance will be reduced significantly and the wind farms will be able to operate sufficiently. In our research, one of the major problems agreed upon in this area of study is the lack of labeled datasets due to security problems related to data sharing. This made solutions depending on deep learning difficult since it depends on a great amount of data. On a local level, we were also faced with the problem of the lack of datasets containing data from Egyptian wind turbines which led to creating a simulation with the available data.

2 Project Description

The primary focus of the project is to detect faults caused by a variation of malfunctions in wind turbines to prevent their occurrence in advance and to predict the wind power generation to ensure maximum utilization of the wind farms.

2.1 Objectives

- Using deep learning techniques and time series analytics to detect fault occurrence and predict potential timing in wind turbines before their occurrence to prevent them.
- Predicting wind power generation within fixed time intervals by using deep learning techniques and time-series analytics for better control and maximum utilization of wind turbines.
- Creating a dataset that simulates local weather conditions and presents predictions for wind power generation that are accurate for Egypt

2.2 Scope

The proposed system is a predictive model that aims to use time-series data, mostly provided by the SCADA system, to detect possible faults in wind turbines. The system shall forecast the power to be generated from the wind turbines by predicting necessary weather variables adherent to a specified dataset.

2.3 Project Overview

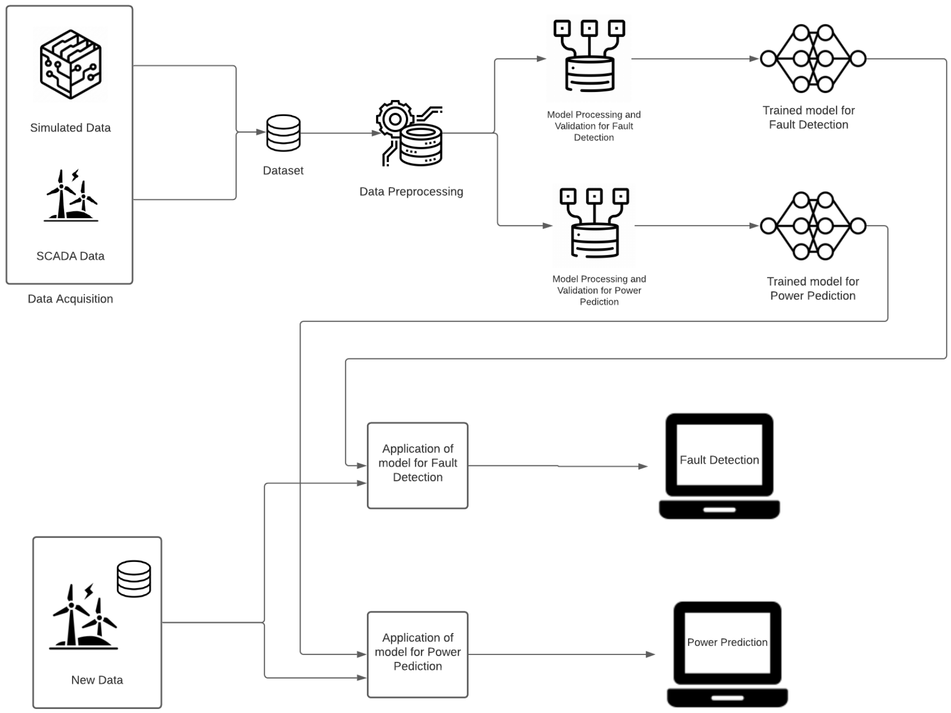

Figure 1: System Overview

The proposed system has a few main steps, those are data acquisition and selection, processing, training model, and finally using a model on new data to detect faults and predict power.
Data prepossessing helps ensure the model will achieve the best result, and that is done through data cleaning and data transformation. Data is then split into training and testing sets. Since the data the proposed system works with is time-series data, the LSTM network is most likely to be used for the model. A software accessible to on-field engineers would display the results reached by the model.

2.4 Stakeholder

2.4.1 Internal

- Backend: Mahi Ayman
- Database Analyst and Datasets: Mariam ElAskary
- Backend: Nour Mahmoud
- Team Leader, Frontend: Zeina Tamer

2.4.2 External

- New and Renewable Energy Authority (NREA) [21]
- Siemens Gamesa Renewable Energy [22]

3 Similar System

3.1 Academic

3.1.1 Fault Detection

Kevin Leahy et al. [5] proposed a system that performs analysis on data acquired from SCADA system. The data came from from "3 MW direct-drive turbine which supplies power to a major biomedical devices manufacturing plant located near the coast in the South of Ireland". The data used was produced over 11 months time From May 2014 until April 2015. Three different datasets were extracted from the SCADA system. These datasets were "operational data status data, and warning data". For operational data, which was the relevant dataset to this paper, the parameters used were “wind speed and ambient temperature, power characteristics such as real and reactive power and various currents and voltages in the electrical equipment, as well as temperatures of components such as the generator bearing and rotor”. The data had to be labelled correctly before training the model. The operational data was split and labelled to “no-fault”, “all faults”, “specific fault” and “fault prediction” datasets. The methodology used for creating the model is SVM. Each dataset was split into 80% for training and 20% for testing after being randomly shuffled. The fault/no fault prediction performance on recall was high reaching 0.9.

Na Song, Xiangzhi Hu, and Ning Li [13] proposed a system that used 6 months worth of data produced from SCADA system from a wind farm located in northwestern China, within half a minute. The features used to train and test models were "Generator front bearing temperature, Generator stator W temperature (W), Motor temperature 3, Outdoor temperature, Active power, Gearbox lubrication oil temperature, 30 second average wind speed, Gearbox high speed bearing temperature, Gearbox oil temperature, Generator slip ring temperature, Gearbox cooling water temperature, Wind wheel speed, and Gearbox low speed bearing temperature". The model used was based on Gated Recurrent Unit (GRU) network.

J.L. Godwin and P.C. Matthews [1] proposed a system that used data from 8 wind turbines that was collected within 10 minute intervals over a period of two years and four months with 10 attributes used to recognize faults. The data was classified into three classes : “no pitch fault”, “potential pitch fault” and “pitch fault established”, which helps in identifying the urgency of the maintenance of wind turbines and the turbines with a reduced remaining useful life (RUL). Data from 4 turbines were kept for training and the other 4 for testing. The features used for building model were "average wind speed, Maximum wind speed, Blade 1 pitch motor torque maximum, Blade 2 pitch motor torque maximum, Average pitch motor torque, Blade 1 pitch angle average, Blade 2 pitch angle average, SCADA pitch fault alarm status, and the absolute difference in torque across pitch motors, the absolute difference in blade angle position". “These attributes were chosen as they fully encapsulate the current operating characteristics of the wind turbine pitch fault system.” The technique used was based on 14 human readable rules generated by the RIPPER inductive rule learner. This model achieved accuracy of 85.50%.

Jian Fu et al. [9] proposed a system that uses a CNN-LSTM model to predict faults in the wind turbines’ gearbox. Both CNN (Convolutional Neural Network) in combination with RNN (Recursive Neural Network) for feature extraction, dimension reduction and classification on the 1-min level data of 90 consecutive days collected by the SCADA system. The dataset consists of 10 variables and 10 consecutive moments. LSTM then uses this reduced data as input and the gearbox bearing temperature as output. When compared to the actual data, the CNN-LSTM model showed the most optimal results for time series prediction of different lengths in comparison to traditional models such as ARMA (Autoregressive moving average model) , DBN (Deep belief network) , BPNN (Back Propagation Neural Network) models.

Mikel Canizo, Enrique Onieva et al.[6] presented a system that uses data gathered from wind turbines during a period of two years. Data is divided in two types: status data (alarms activations and deactivations) and operational data, which represent the performance of the wind turbines within 10 minutes intervals. There are 448 different alarm types and 104 parameters concerning the operational data. It predicts faults in wind turbines that consists of three modules "(i) A predictive model based on the Random Forest algorithm. (ii) A monitoring agent that makes fault predictions for the next hour every 10 minutes. (iii) Visualizing the given predictions on a dashboard." Concerning the accuracy and sensitivity the results were higher compared to other models in contrast to specificity meaning that it has more false positives.

Jan Helsen, Gert De Sitter, and Pieter Jan Jordae [4] presented the challenges of monitoring and analyzing wind turbine data. The paper suggests the use of "a big data based approach for integrated no-sql data-storage and data-analytics platform". The paper discusses the approach to sore data in order to perform integrated analysis, and discusses a strategy for early faults detection in bearings which are components used in systems that rotate, which is one aspect of data-intelligence. The paper suggests that early detection in possible failures in bearings is a main aspect to reach a better maintenance strategy for wind farms. The paper discusses these challenges and requirements upon a used dataset that was acquired of monitoring offshore wind farms on the span of four years.The paper, however, does not mention the exact models built for bearing temperature detection, which if analyzed properly could be indication of possible failures.

Reihane Rahimilarki et al. [12] provided two CNN structures on data simulation based on a 4.8 MW wind turbine benchmark that has a generator torque (g) output. The dataset consists of 120 records of g saved in time series signal format, with a noisy sensor, for gathering the data of g of a variance of 0.3% and mean value of 0 to make the conditions more similar to reality. The sampling time is 1 second and each record contains 4900 samples. The time series raw data is first converted into 2-D greyscale images building a n×n×1 matrix, in which 1 is the quantity of the channels. The first suggested structure is CNN with One convolutional Layer and the second is CNN with Two convolutional Layer. It was proven that the CNN with Two convolutional Layer performed better reaching an accuracy of 100% with 45 kernels.

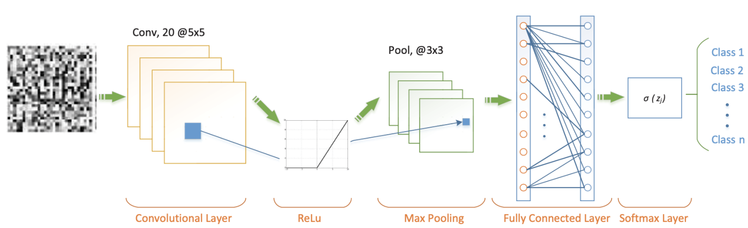

Figure 2: CNN with One convolutional Layer[12]

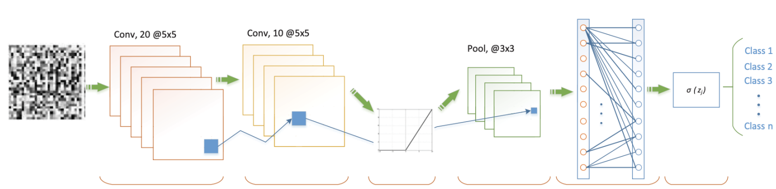

Figure 3: CNN with Two convolutional Layer[12]

Yirong Liu, Zidong Wu, and Xiaoli Wang [15] proposed a system for early warning of possible faults in wind turbine generator and gearbox. The data used was collected from a SCADA system from a wind farm in Inner Magnolia (China). The paper uses eXtreme gradient boosting (XGBoost) algorithm to set the normal temperature regression prediction model of wind turbine components. The parameters used for predicting gearbox temperature change are "gearbox low speed bearing temperature, active power, gearbox high speed bearing temperature, generator speed, impeller speed, ambient wind speed, cabin temperature, and ambient temperature". The model is then used to predict temperature in key parts of the wind turbine. It was noted that the residual from the XGBoost model was significantly less than a the model used as control, SVR. The MAE for SVR and XGBoost was 3.415 and 0.335, respectively.

Pedro Henrique Feijo de Sousa et al. [8] focused in this paper on the fault detection in electric generators in the wind turbines namely the English Squirrel Cage Induction Generator (SCIG), a generator known for being small in size and not having rings or brushes contributing to the lower cost of maintenance and installation. The performance of the following classifiers: Bayes, SVM, Optimum Path Forest (OPF), and K-Nearest Neighbor (KNN) are used and compared for the optimal results. The average results of all classifiers are as follows, "using HOS, KNN reached 86.75% of accuracy rate, then OPF with 88.41%. The highest results were those of SVM and Bayes, with 94.44% and 95.62% of hit rate respectively". Bayes was also more able to identify true positives and negatives, since its specificity and sensitivity are superior than other methods.

Jyh-Yih Hsu et al. [14] proposed a system that predicts maintance needs by analyzing 2.8 million sensor data collected from 31 wind turbines from 2015 to 2017 in the ChangHua Coastal Industrial Park, Taiwan. This paper used both statistical process control charts and machine learning techniques for prediction in order to provide robust results. Four categories of wind turbine faults were identified by statistical program control, and those are rotary blades, gearboxes, generators, and hydraulic oil systems. Two machine learning algorithms, decision tree and random forest classifications, were used to predict irregularity in wind turbines. High level accuracies were indicated from both models with K-fold cross-validation, 92.68% for the decision tree model, and 91.98% for the random forest model.

3.1.2 Power Prediction

Haroon Rashid, Waqar Haider, and Canras Batunlu [16] proposed a model that predicts power of wind turbines using random forest regression algorithm. The data used was data produced from SCADA system on a 13 months period from a 2 MW wind turbine in a wind farm in France. The input parameters for the model are wind direction, wind speed and outdoor temperature. The estimated mean absolute errors for the proposed model were 3.6% and 7.3% for 0.4 and 0.2 capacity factors, respectively.

Meijie Liu, Peng Qiu, Kai Wei [11] present a system that predicts wind speed of wind power system in a short time using a GRU (Gated Recurrent Unit) model on a data set containing 1182 wind speed sampling nodes. After preprocessing, "there are 811 training set data, 372 test set data, 13 input variables, and 1 output variable". The GRU improves the long-term memory ability of the time series, selecting the data of the first 10 time scales of wind speed and the output of the model is the change rate of the next time scale relative to the previous time scale. When the predicted wind power was compared to the true value the mean square error of the two sequences is 0.98, making the model's prediction near value of wind speed.

4 What is new in the Proposed Project?

This project aims to build a model using datasets produced from local wind turbines that adhere to Egypt's climate but due to the scarcity of available wind turbine data collected locally, SCADA data from various sources could be used to tailor similar results.

5 Proof of concept

5.1 Fault Detection

As a start, we worked on two datasets: the event dataset and the SCADA dataset[20]. The event data had a label of whether there is a fault in the wind turbine or not. The SCADA dataset, however, had features only. We wanted to label the SCADA data from the event data. Based on a paper we read, we tried to use a batching system to label the SCADA data to create a classification model next. The results from the batching system were not correct and all the labels indicated that no fault has happened, and that does not align with the event data.

We, then, decided to use simple machine learning methods on the event dataset to try and classify the existence of faults, without prepossessing. We wanted to see how the machine learning algorithms mentioned in papers initially performed on an event dataset. We used KNN and SVM, the accuracy was 0.88 and 0.79, respectively.

We, however, noticed that time-series data does not work well with those machine learning algorithms. The best option was to move to neural networks. Based upon the papers and researches we read, the LSTM network, which is a recurrent neural network architecture that has a memory cell, allows better performance. That, however, will not work without a labeled dataset. However, LSTM can be applied for feature forecasting that can be a step in fault detection. Below are the results of forecasting one feature from the SCADA data.

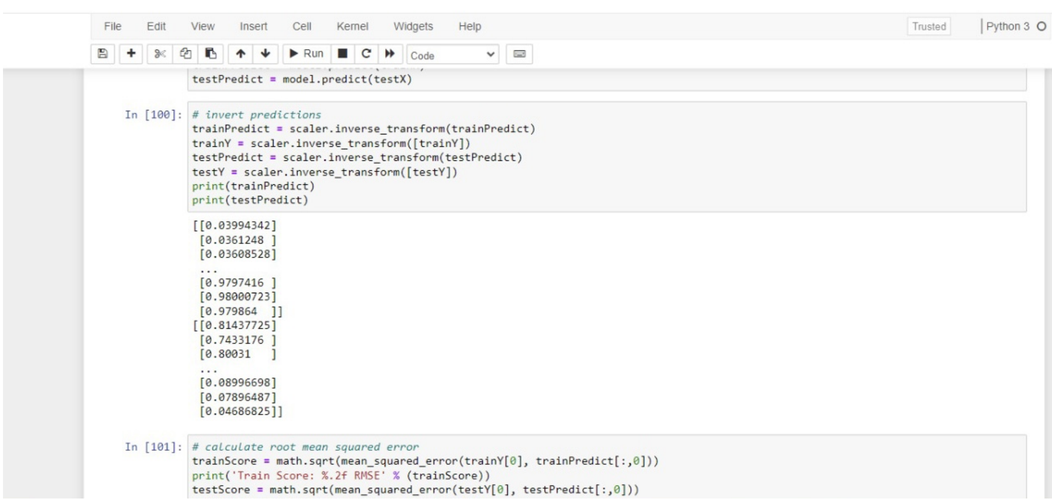

Figure 4: Forecasting

```
 ...
 [0.08996698]
 [0.07896487]
 [0.04686825]]

n [101]: # calculate root mean squared error
trainScore = math.sqrt(mean_squared_error(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = math.sqrt(mean_squared_error(testY[0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore))

Train Score: 0.10 RMSE
Test Score: 0.10 RMSE

n [102]: # shift train predictions for plotting
trainPredictPlot = numpy.empty_like(dataset)
trainPredictPlot[:, :] = numpy.nan
trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict

n [103]: # shift test predictions for plotting
```

Figure 5: Forecasting

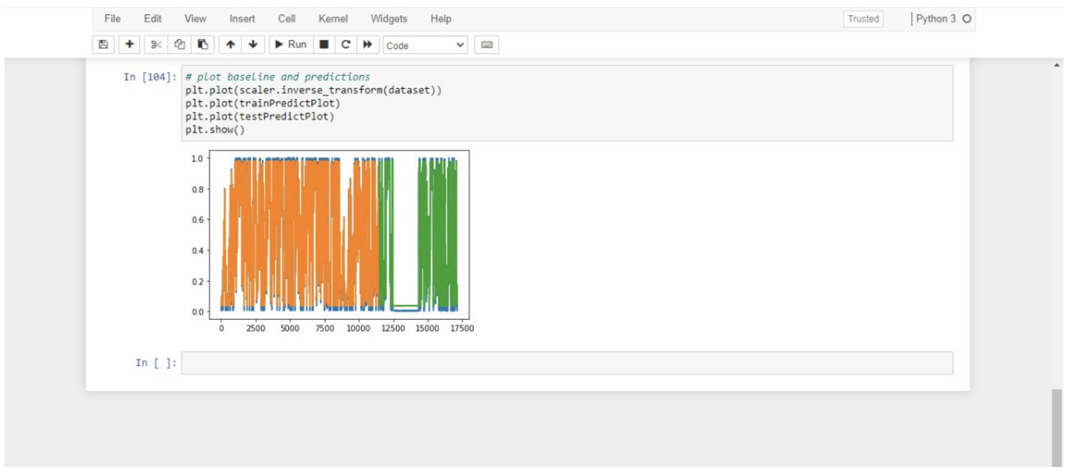

Figure 6: Forecasting

5.2 Power Prediction

For power prediction, since we are also working on time-series data, we will use LSTM network for with multiple. The model is to be tested on SCADA system from a wind turbine in Turkey[7].

6 Project Management and Deliverables

6.1 Deliverables

- A web application that alerts field engineers of future deficiencies that may occur in the wind and reports of the predicted wind power to be generated.
- Software Requirement Specification document
- Software Design document
- Python backend

6.2 Tasks and Time Plan

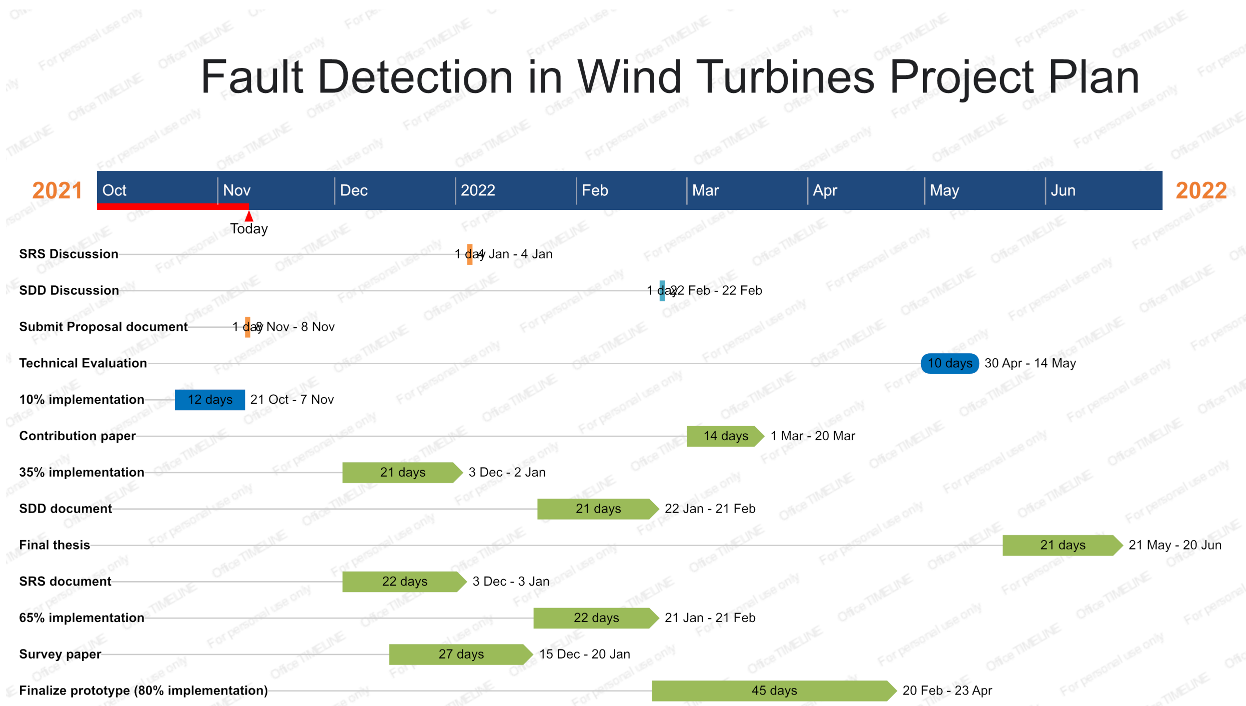

Figure 7: Timeplan

7 Supportive Documents

7.1 Datasets

In the many papers available, a lot of different datasets were used for developing models for detecting fault detection. This data was collected from different places, like China, Ireland, and many other places. For this paper, we used different datasets. For fault detection, we initially worked on a dataset available on Github that has "time-stamped operational data for the turbine. The timestamps are at 10-minute intervals which represent the average of the sensor readings over that period." There existed also an Event dataset that had a label of occurrence of faults. [20]

For power prediction, another dataset used was data collected from the SCADA system from a wind turbine in Turkey. The data was available on Kaggle [7].

7.2 Contacting authors

Nour Nour Mahmoud Seif EL Nasr Mahmoud ElGarhy <nour1812880@miuegypt.edu.eg> Wed, Nov 3, 9:35 PM (17 hours ago)
to andrew-kusiak

Hello Kusiak,

I am a senior student at faculty of computer science at Misr International University and I'm currently working on my graduation project which is about forecasting faults in wind turbines. It would be of great help if you can share with me the dataset you worked on for the paper "The prediction and diagnosis of wind turbine faults".

•••

Figure 8: Author 1

Nour Nour Mahmoud Seif EL Nasr Mahmoud ElGarhy <nour1812880@miuegypt.edu.eg> Tue, Nov 2, 4:10 PM (2 days ago)
to kevin.leahy

Hi Leahy,

I am a senior student at faculty of computer science at Misr International University and I'm currently working on my graduation project which is about forecasting faults in wind turbines. It would be of great help if you can share with me the dataset you worked on for the paper "Diagnosing wind turbine faults using machine learning techniques applied to operational data".

Thanks in advance.
Regards,
Nour Elgarhy

Figure 9: Author 2

Nour Nour Mahmoud Seif EL Nasr Mahmoud ElGarhy <nour1812880@miuegypt.edu.eg> 8:43 AM (6 hours ago)
to haroon.rashid

Hello Rashid,

I am a senior student at faculty of computer science at Misr International University and I'm currently working on my graduation project which is about forecasting faults in wind turbines and power prediction. I came across your paper "Forecasting of Wind Turbine Output Power Using Machine learning" and found it really insightful. It would be of great help if you can share with me the dataset you worked on for the paper.

Thanks in advance

Regards,

Nour Elgarhy

Figure 10: Author 3

8 References

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