ADAPTIVE TURBINE CONTROL FOR OPTIMAL OUTPUT USING AI

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Abstract

This project focuses on the development of a fuzzy logic-controlled blade angle adjustment system for wind turbines along with wear-and-tear monitoring. The primary aim is to maximize energy output while minimizing operational stress and long-term maintenance costs. The system leverages fuzzy logic principles to dynamically adjust blade angles based on multiple parameters, including wind speed fluctuations, blade angle change rates, and operational stress.

Keywords: WindTurbine, BladeAngle, PowerOutput, Fuzzy Logic, Random Forest

I. INTRODUCTION

A. Problem Statement

The efficiency and longevity of wind turbines has been a concern for a long period of time, leading to huge operational cost and manual labor. There is a need for a smart, prediction model system that optimizes turbine blade angles to balance power generation, reduce wear and tear and improve the overall durability of wind turbines under varying wind conditions.

B. Background

Wind energy is a key player in the global shift towards renewable energy, but optimizing wind turbine performance remains challenging due to fluctuating wind conditions. Traditional turbine systems rely on fixed or infrequent blade angle adjustments, leading to inefficiencies in power generation and increased mechanical stress. These issues result in higher maintenance costs and reduced operational lifespans. Recent advancements in AI-driven adaptive systems, such as fuzzy logic and machine learning, offer solutions for real-time optimization but often come with high computational costs. To address this, lightweight and intelligent control mechanisms are emerging as a practical alternative. These systems aim to enhance power efficiency, minimize wear and tear, and extend turbine longevity, making wind energy more sustainable and economically viable.

C. Motivation

With the rising concern over carbon footprints and environmental sustainability, wind energy stands out as a cost-effective and promising renewable energy source. However, its potential remains underutilized due to suboptimal operational efficiency and mechanical stress on turbines. Motivated by these challenges, we have developed an AI-assisted wind turbine system designed to optimize power output while minimizing wear and tear. By integrating adaptive algorithms and prediction models, this innovative approach ensures enhanced efficiency, reduced maintenance costs, and a sustainable, economically viable solution for renewable energy generation.

D. Research – Gap:

1. Limited Prediction Adaptive mechanism.
2. Integration of wear and Tear Metrics.
3. Fuzzy Logic Systems for multiparameter controls.

E. Math behind it:

The aerodynamic performance of wind turbine blades is critically influenced by the flow angle (ϕ), angle of attack (α), and blade pitch angle (θ). These parameters are interrelated and essential for optimizing lift, minimizing drag, and ensuring efficient energy conversion.

1. Flow Angle

$$\tan^{-1}\left(\frac{V_{\omega}}{\omega r}\right)$$

2. Angle of attack (α):
   It is critical for determining the aerodynamic performance of the blade, as it directly affects the lift-to-drag ratio.
3. Blade pitch angle (θ):

$$\boldsymbol{\Theta} = \boldsymbol{\phi} - \boldsymbol{\alpha}$$

II. METHODOLOGY

The goal of this project is to develop a prediction model using AI to optimize the blade angle of a wind turbine for maximum power output while minimizing wear and tear. This is achieved by processing historical data and using machine learning techniques to predict the best possible blade angle adjustments.

A. *Hardware:*

1. Wind Turbine Prototype: Includes blades, a rotor, and a hub, modelled to simulate real-world turbine dynamics.

2. Servo Motor: Controls the blade angles dynamically based on AI predictions.

3. Microcontroller: Acts as the central processing unit for data collection and servo motor control (We have used Arduino).

B. *Data Collection:*

Historical Data:

- The project uses a historical dataset containing wind turbine performance metrics, including:
  Wind Speed**:** Recorded wind speed at various intervals.
  Blade Angle Recorded blade angles during turbine operation.

  Power Output (PPO): The energy generated by the turbine, which is impacted by wind speed and blade angle.

  Operational Stress: An estimate of mechanical stress or wear, based on power output and other variables like rotor speed.

C. *Feature Engineering:*

Blade Angle Change Rate ($\Delta\theta$**)**:
The rate of change in blade angles from one time step to the next. This is calculated as:

$$\Delta\theta = \theta_{\text{current}} - \theta_{\text{previous}}$$

Wind Speed Fluctuations (ΔV_w):
Changes in wind speed between consecutive data points. This helps understand how quickly wind conditions change, impacting the blade angle decisions.

Operational Stress:
Derived from the power output and modeled based on expected mechanical loads and efficiencies of the wind turbine.

D. *AI Model Development:*

Supervised Learning: A regression model is chosen, as we are predicting continuous values for blade angles.

Algorithms Used: Random Forest, Gradient Boosting, and Support Vector Regression (SVR) are tested for predictive accuracy and robustness.

1. *Training the Model:*

The historical dataset of 2018 is split into training and testing sets (e.g., 80% training, 20% testing).
Features like wind speed, blade angle change rate, and operational stress are used to predict the optimal blade angle at each time step.

Model Evaluation:
Cross-Validation: K-fold cross-validation is used to validate model performance.
Metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score are used to evaluate prediction accuracy.

2. *Blade Angle Prediction*

1. Feature Inputs:

Wind Speed**:** Used to predict the fluctuation of wind speed.

Blade Angle Change Rate ($\Delta\theta$): Helps to determine the rate at which the blade angles need to be adjusted based on previous readings.

Operational Stress: An estimate of wear and tear based on power output.

2. AI Output:

The model predicts the optimal blade angle adjustment based on the inputs to maximize power output and minimize wear and tear.

3. Wear and Tear Prediction:

The AI model also predicts the **Wear and Tear Index (WTI)**, based on the predicted blade angle adjustments and wind speed fluctuations.

3. *Methodology for Optimization*

1. Predicting Blade Angle Adjustments:

The model outputs an adjusted blade angle (θ) for each time step.
If the predicted wear and tear index (WTI) is high, the blade angle is reduced to decrease operational stress. If the WTI is low, the angle is increased to optimize power production.

2. Power Output Maximization:

The AI model is trained to maximize power output (PPO) by adjusting the blade angle based on wind speed and operational stress.
A mathematical relationship is maintained to calculate the theoretical power output based on the blade angle and wind speed.

4. RESULTS AND FINDINGS:

MAE (Mean Absolute Error):

- This value tells how far, on average, the predicted blade angles were from the true values (actual angles).
- A **lower MAE** would indicate that the model's predictions are generally closer to the true values, which means the model is doing well in estimating the optimal blade angle.

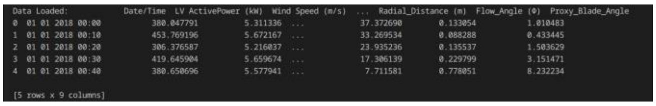
MSE (Mean Squared Error):

- This metric indicates how much squared error the predictions have.
- A **lower MSE** means fewer large errors, but MSE is sensitive to large deviations, so even a single large error can increase the MSE significantly.

The Random Forest prediction model that we have used give the following report:

• Mean Absolute Error (MAE): 0.4145
• Mean Squared Error (MSE): 0.2694
• R2Score: 0.9575

A Small Section of the output that we have received when we ran the code is:



```
Data Loaded:          Date/Time  LV ActivePower (kW)  Wind Speed (m/s)  ...  Radial_Distance (m)  Flow_Angle (Φ)  Proxy_Blade_Angle
0  01 01 2018 00:00           380.047791          5.311336  ...            37.372690        0.133054           1.010483
1  01 01 2018 00:10           453.769196          5.672167  ...            33.269534        0.088288           0.433445
2  01 01 2018 00:20           306.376587          5.216037  ...            23.935236        0.135537           1.503629
3  01 01 2018 00:30           419.645904          5.659674  ...            17.306139        0.229799           3.151471
4  01 01 2018 00:40           380.650696          5.577941  ...             7.711581        0.778051           8.232234

[5 rows x 9 columns]
```

5. CONCLUSION:

1. Dataset and Variables Used**:**

We used a dataset containing several key variables like wind speed, blade angles, wind direction, and theoretical power curve.

The primary goal was to predict the optimal blade angle to maximize power output and reduce wear and tear.

Wind Speed (m/s), Proxy Blade Angle, and Operational Stress (represented by LV Active Power (kW)) were the key features used to make predictions.

2. Model Development:

We choose fuzzy logic algorithm for the following aspects:

- Wind speed fluctuation
- Blade Angle Change Rate.
- Operational Stress

Based on these inputs, we derived a Wear and Tear Index (WTI), which is used to adjust the blade angle to either increase or decrease the blade angle depending on the wear. The fuzzy logic system generated rules such as:

If wind speed fluctuation and blade angle change rate are high, then the wear and tear index is also high, indicating the need for a lower blade angle.

If both parameters are low, the wear and tear index is low, suggesting an optimal or higher blade angle.

6. REFERENCES

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