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Fault Detection in Wind Turbines using Weather Decomposition

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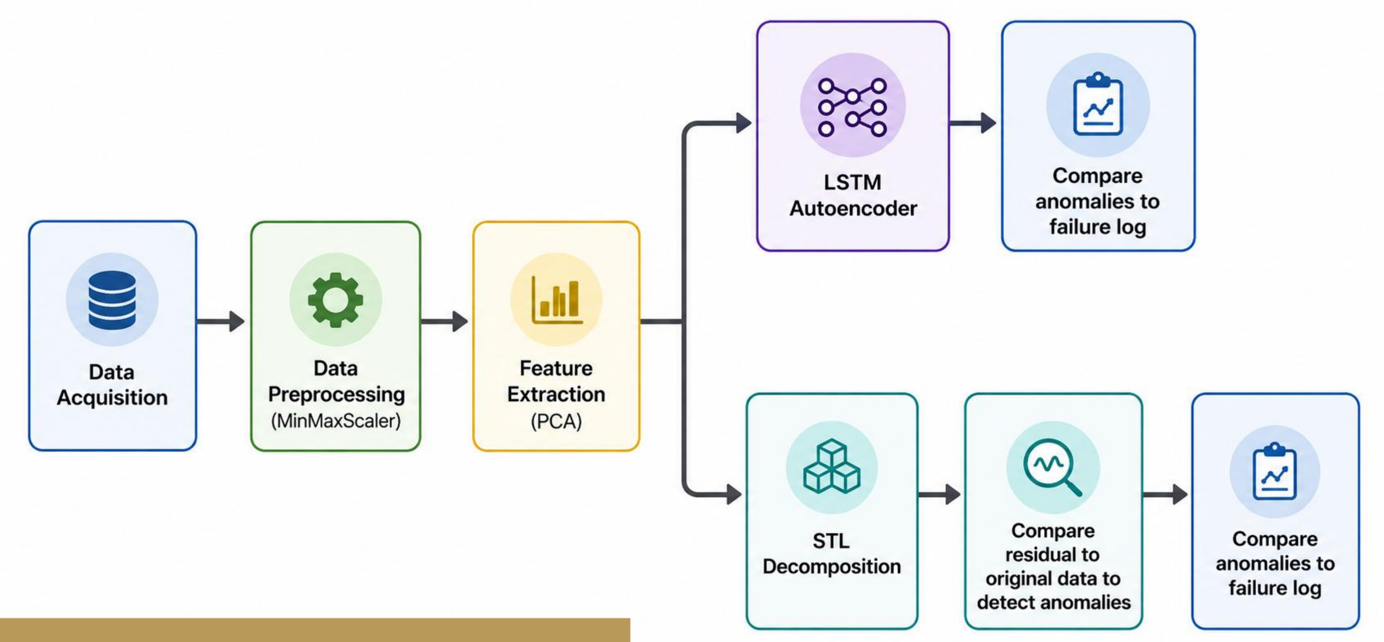
INTRODUCTION & AIM

Wind turbines have been deployed in both offshore and onshore locations around the world, representing a crucial component of renewable energy infrastructure. With the increasing diversity and geographical spread of wind turbine installations comes the significant challenge of understanding and mitigating weather effects on these systems' long-term operational life and performance capabilities. Weather conditions play a fundamental role in determining the power output of wind turbines. During periods of strong wind activity, substantially more electrical energy is generated compared to calm conditions when wind speeds are minimal or insufficient. Consequently, proactive maintenance strategies must be implemented for turbines experiencing prolonged periods of low wind exposure to minimize operational downtime and maintain efficiency standards.

METHOD

The paper examines the relationship between weather conditions and wind turbine failures through advanced analytical methods. Principal Component Analysis (PCA) is employed to reduce the dimensionality of complex datasets and identify the most significant features influencing turbine performance. The Seasonal and Trend decomposition using Loess (STL) algorithm is applied to weather data to separate time series information into distinct trend, seasonal, and residual components.

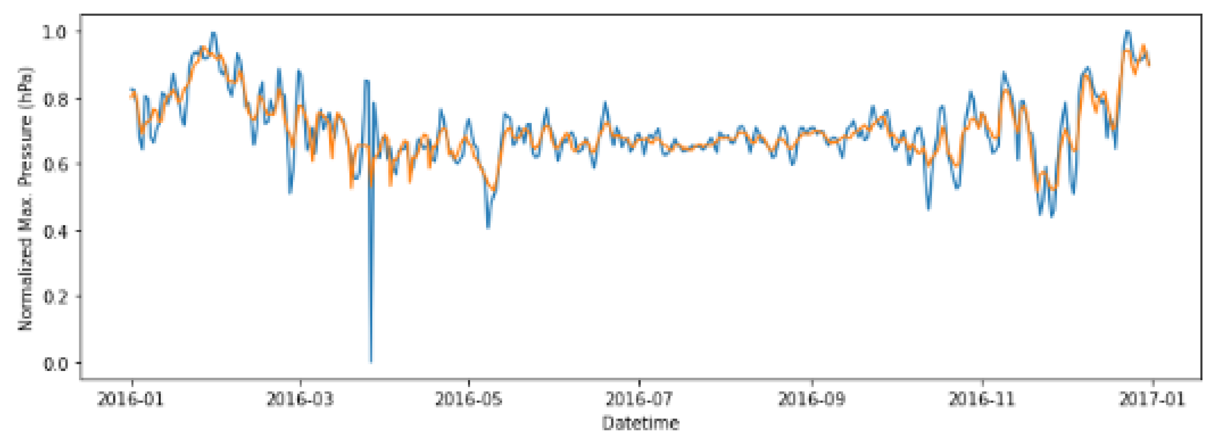


RESULTS & DISCUSSION

SCADA Data is rarely available in public repositories, so weather data was selected as a practical alternative due to its accessibility. Since LSTM had previously demonstrated strong performance on SCADA data, it was first evaluated on weather data to assess whether it could yield comparable results. However, LSTM failed to meet expectations, producing a high rate of false positives. This limitation prompted the adoption of STL decomposition, which was applied to extract more meaningful components from the time-series data. STL decomposed the weather data into three components: Seasonal, Trend, and Residual. This decomposition not only facilitated visualization of the data's overall behavior but also revealed the extent to which noise affected certain features. The weather dataset comprised 44 features recorded at 10-minute intervals. Given the high dimensionality of the feature space, PCA was applied to reduce the number of features to a more manageable set.

Following Dimensionality reduction, three preprocessing steps were applied to each feature individually: Aggregation, Aggregation Normalization, and STL decomposition. Since the 10-minute sampling rate produced a large number of instances, all readings within a given day were consolidated into a single daily value through Aggregation, thereby reducing the dataset size and improving model efficiency. However, this grouping caused feature values to become unacceptably large, necessitating Aggregation Normalization. This was performed using Min-Max Scaling, which rescales each feature to the range [0, 1] by subtracting the feature's minimum value and dividing by its range. An anomaly detection threshold was then derived by computing the mean and standard deviation of the residual component, flagging any value exceeding this threshold as an anomaly.

Collectively, These methods achieved early failure prediction windows ranging from 7 to 15 days and attained precision scores between 0.40 and 0.75. The STL-based pipeline proved particularly effective at detecting failures in the Generator, Generator Bearing, and Hydraulic Group components. The plot shows the relation between the original and residual data.



CONCLUSIONS

Obtaining complete SCADA data is often difficult, limiting the development of wind turbine failure prediction models. Since weather data is more accessible, it can be used to investigate factors affecting turbine components and support early fault detection. This study examined the relationship between weather features and wind turbine failures using STL decomposition, where the residual component was employed for failure prediction. Experimental results showed that failures could be detected up to 15 days in advance.

FUTURE WORK/ REFERENCES/ACKNOWLEDGMENT

Future work will explore weather data from different locations and investigate advanced approaches such as STL-Attention-based LSTM (STL-ATTLSTM), which enhances LSTM performance by integrating STL decomposition and has shown promising results in applications such as vegetable price forecasting.

This work is a continuation of : Ayman, Mahi, et al. "Fault detection in wind turbines using deep learning." *2022 2nd International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC)*. IEEE, 2022.