FAULT PREDICTION FOR RENEWABLE ENERGY APPLICATIONS USING DEEP NEURAL NETWORK

Daniel F. Aragones
MS Electrical Engineering
University of Puerto Rico, Mayaguez
Faculty Advisor: Dr. Vidya Manian

Abstract

Energy generation systems have a complex structure and hence detecting faults in these systems is challenging. In this research, we present a data-driven approach to predict faults from sensor data. While models using autoencoders, and graph convolutional neural networks is presented in the literature, the goal is to develop an interpretable neural network model for fault prediction. A deep learning neural network model is developed to predict faults in wind turbine blades dataset and photovoltaic microgrid dataset. Standard normalization is applied as a preprocessing step for both datasets. Principal components analysis of the photovoltaic dataset is presented. The model presented achieves state-of-the-art performance in fault prediction.

Introduction

Renewable energy sources such as solar, wind, and geothermal when integrated into a microgrid system although reliable, can give rise to technical faults that damage the energy generation process.

There are two types of fault detection approaches: model-driven and data-driven. Model-driven employs a physical model, while data-driven is based on control and data acquisition and can be implemented using Deep Learning (DL) models.

Deep Learning models are a part of Artificial Intelligence (AI) neural network models.

A DL neural network has several hidden layers of nodes between the input layer and output layer of nodes. More complex neural networks such as Autoencoders (AE) and Graph Convolutional Networks (GCNs) have been proposed for identifying and diagnosing faults in various process monitoring systems.

Recurrent Neural Networks, more specifically Long Short Term Memory (LSTM) models have been used for prediction in time series datasets that predominantly occur in microgrid systems.

The advantage of integrating temporal information is useful in Smart Microgrid (SMG), as the data varies with time. Temporal - GCN (T-GCN) learns spatiotemporal data from Supervisory Control and Data Acquisition (SCADA) sensor data, via the Gated Recurrent Unit (GRU). This method has shown superior performance over using GCN-AE model.

T-GCN AE has been shown to have a better performance in fault detection producing a lower False Alarm Rate (FAR) and higher Fault Detection Rate (FDR).

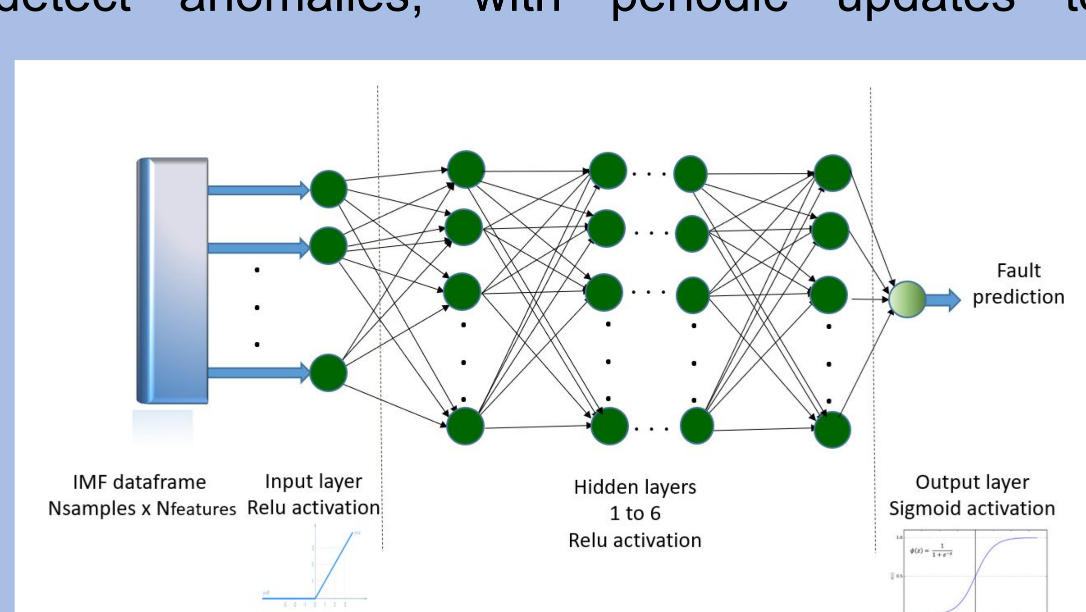
In the era of developing interpretable and explainable AI, we propose to develop a deep neural network architecture for fault detection in wind turbine and PV systems.

Objectives

- Develop a neural network capable of detecting whether a turbine or microgrid is operating in optimal conditions or has an anomalous state
- Apply a deep learning neural network (DNN) model to detect faults in a wind turbine microgrid system
- Evaluate the model using statistical metrics: Accuracy, Mean Square Error (MSE) and Mean Absolute Error (MAE)

Methodology

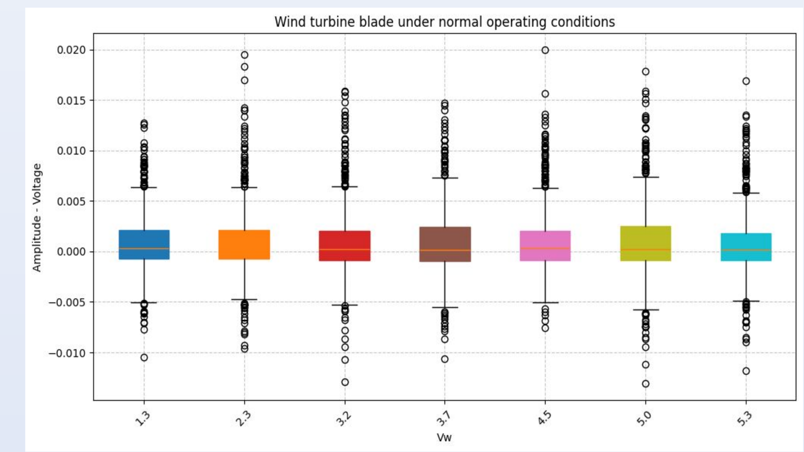
- The methodology for developing neural networks begins with defining the problem and collecting data.
- The data is cleaned by normalizing and applying other essential preprocessing methods, such as dimensionality reduction
- The dataset is now transformed to a feature set that has labels assigned to each category.
- The labeled dataset is then divided into training, validation, and testing sets.
- The neural network model is designed by choosing the number of layers, number of neurons in each layer, and the activation function implemented by each neuron or node
- The model parameters to be set are learning rate and number of epochs for training
- Once the model is trained and converges to a minimum classification error rate, it is deployed in production, integrating into the renewable energy system to detect anomalies, with periodic updates to maintain its performance.

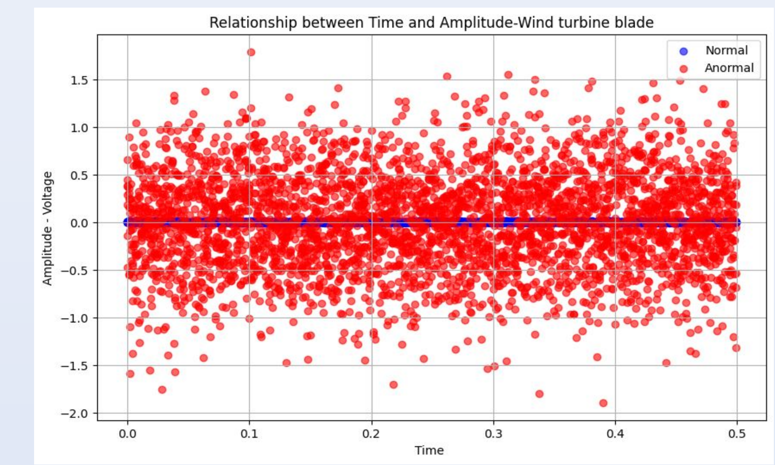


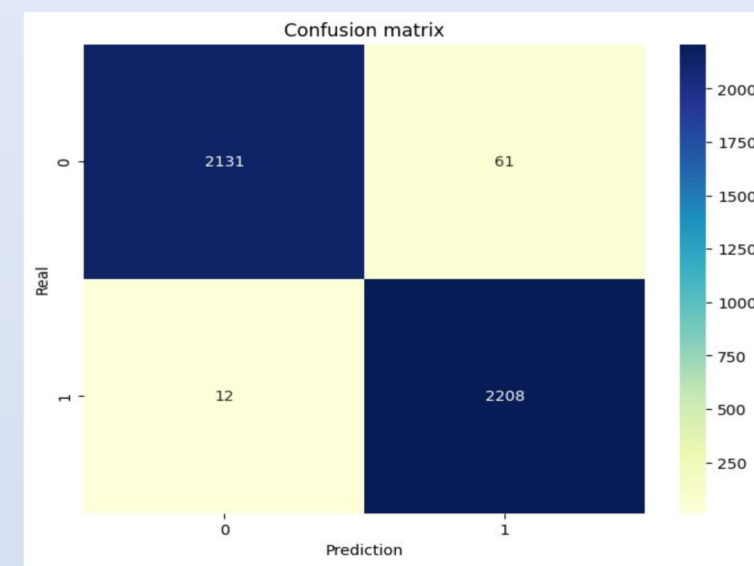
Deep Neural Network (DNN) Architecture

Results

Wind Turbine Blade (WTB)

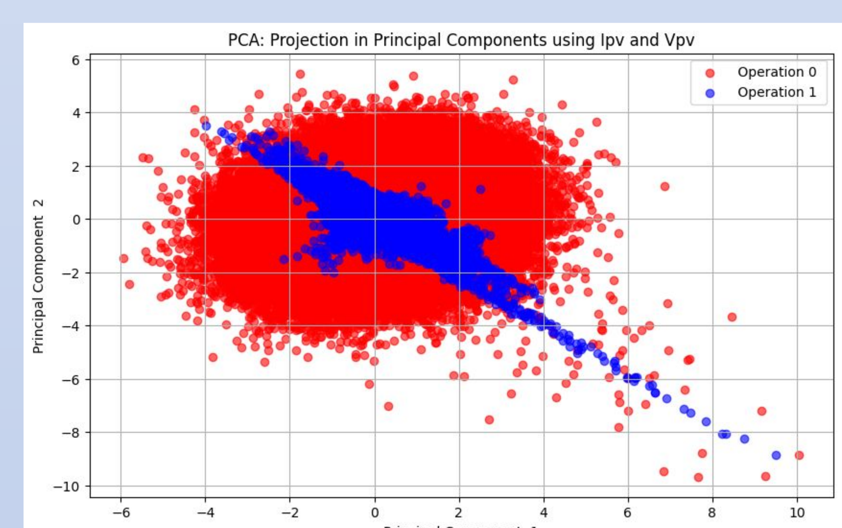


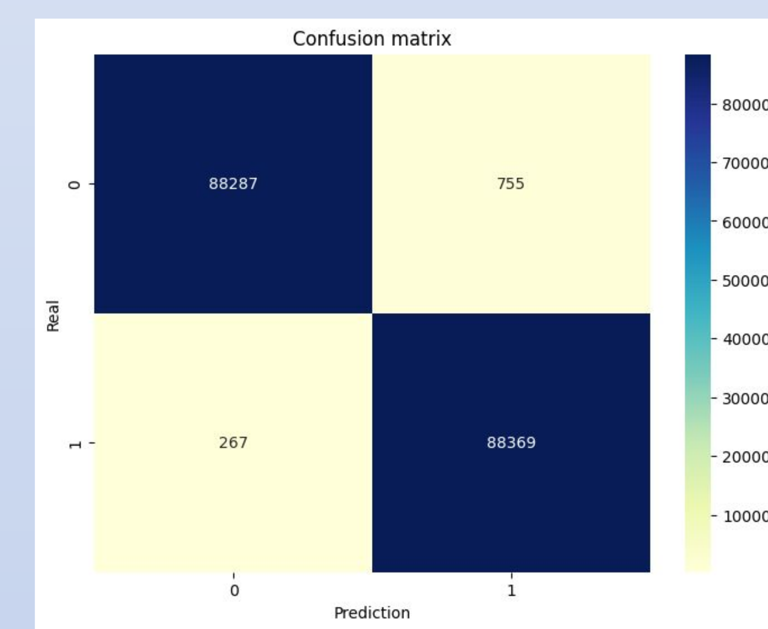




Datasets	MSE	MAE	Prediction Accuracy (%)
Training	0.01557	0.03331	98.185
Validation	0.01750	0.03484	98.030
Testing	0.01462	0.02614	98.345

Grid-connected photovoltaic systems under MPPT modes





Dataset	MSE	MAE	Prediction Accuracy (%)
Training	0.00382	0.00753	99.5385
Validation	0.00397	0.00775	99.5198
Testing	0.00487	0.00892	99.4248

Discussion

In a wind turbine, the faults are due to blade vibration, erosion, and weather conditions which affects the power generation. In our implementation, we used 500 data points of normal voltages, and added Gaussian noise with N(0,0.5) to create faulty data, resulting in 500 faulty data, totaling 1000 samples. The data is divided into 63% for training and 33% for validation and testing with a 5 fold cross validation. The DNN model gives a fault prediction accuracy of 98.35% and 99.42% on the testing set. In the case of the PV grid dataset, voltage, current measurements in the 3 phases are used as features. The DNN performance are evaluated with MSE, MAE, and prediction accuracy.

Conclusions and Outlook

DNN models were successfully used to predict faults in wind turbine blades dataset and PV datasets. The fault was simulated by adding Gaussian noise to the normal dataset.

A DNN is an interpretable and explainable model and it has to be tested with other faults such as blade erosion, mass imbalance, and cracked blades. The importance of each fracture or crack on the power generation outcome has to be evaluated.

A similar approach will be developed for photovoltaic microgrid system evaluation.

References

[1] M. Manogaran, "Human activity recognition using wearable sensors," Mendeley Data, V4, 2020. [Online]. Available: https://data.mendeley.com/datasets/5d7vbdp8f7/4

[2] Z. J. Hafeez, "Eye State Classification Dataset," Mendeley Data, V1, 2020. [Online]. Available:https://data.mendeley.com/datasets/n76t439f65/1.

[3] X. Yu, B. Tang, and K. Zhang, "Fault diagnosis of wind turbine gearbox using a novel method of fast deep graph convolutional networks," IEEE Transactions on Instrumentation and Measurement, vol 70, pp. 1–14, 2021.

[4] Z. Chen, J. Xu, T. Peng, and C. Yang, "Graph convolutional network-based method for fault diagnosis using a hybrid of measurement and prior knowledge," IEEE transactions on cybernetics, vol. 52, no. 9, pp..

Acknowledgment

We thank the Artificial Intelligence Image Group (AIIG) Laboratory, located in CID -F221, Department of Electrical and Computer Engineering for providing the DNN architecture to complete the results for this work. https://www.uprm.edu/aiig/