Employment of ANN for Predictive Motor Maintenance and Bearing Fault Detection Using Park's Vector Analysis

B. Aadhi Aadhavan and V. Valli Meenaa| Prof. Sujatha R.| SENSE

Motivation/ Introduction

Predictive maintenance is an emerging concept that is gaining mainstream popularity in industrial automation. It involves continuous monitoring of the machinery's health, status, and performance in real-time. Critical machinery such as three-phase induction motors is being used widely in industrial processes. However, they are subjected to many electrical and mechanical stresses due to their long operating times. The proposed model employed MCSA by plotting Park's vector analysis graph to predict motor health. This graph would then be fed as the input to an artificial neural network (ANN) for automated classification of the healthy or unhealthy motor.

SCOPE of the Project

Bearing faults account for the highest faults in the induction motor. If the faults go unnoticed, they can result in motor failure, which generates economic losses. Thus, the tracking of motor health becomes ineluctable. The proposed model has managed to acquire an accuracy >99% in the test set, thus triumphing over other predictive maintenance methods.

Methodology

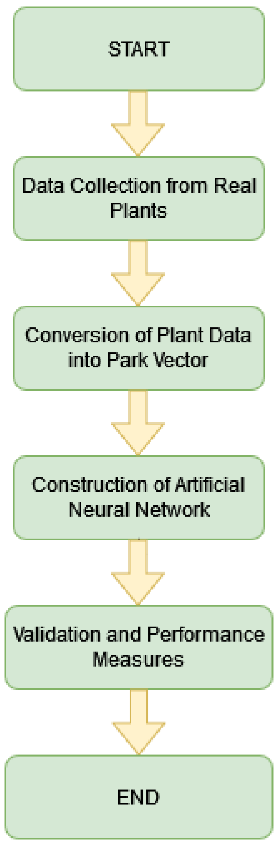


Figure 1. Process Flow

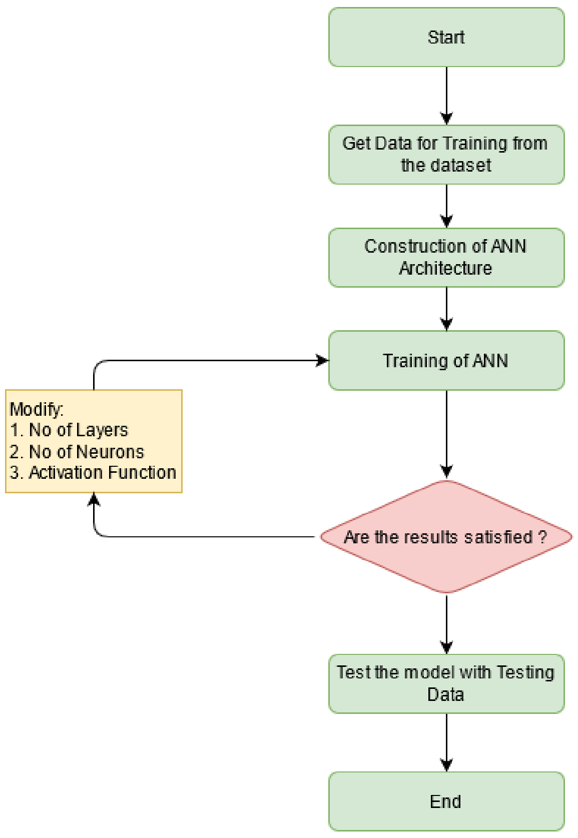


Figure 2. Network of ANN

Figure. 1 depicts the block diagram of the overall methodology involving its sub processes. Primarily, the raw data is collected from real plants and converted into Park Vector images. Afterward, a simple ANN structure with three Dense Layers is utilized in classification processes. Raw data consisting of 3 phase stator current of the motor is being collected from three different real industrial plants. The raw dataset features include Motor ID, Electrical Team, 3 phase of currents, Vibration Team. Conversion of Plant Data into Park Vector involves a series of following processes: 1) Plotting Actual Data of every motor 2) Rescaling the plotted Currents against time 3) Calculating the stator currents plot 4) Envelope and plot stator Is_D and Is_Q component trajectory. The Park vector Analysis gets its input from the 3 phases of the motor, and it plots it as a graph. The shape of the graph represents the health of the motor. A well-rounded circular graph represents a healthy motor, whereas an elliptical graph represents a motor that requires maintenance. The dataset comprises 36 images, whereas 28 park vectors are used for training, and eight are used for healthy and unhealthy testing. After collecting the dataset, the ANN architecture is constructed with layers of different inputs and activations functions. Then the trained data is fed into the ANN model. We achieve the training accuracy; we can end the training process and move the model to test it with testing data if the results are satisfying. Else it is required to fine-tune the model more to achieve the desired results. The whole flow of the network is being explained in Figure 2. The classification is controlled by a simple Artificial Neural Network structure with three Dense Layers with 8, 4, and 1 unit. The first and second layer has an activation function of ReLU, and the final classification layer has an activation function of Sigmoid. Rectified linear unit (ReLU), sigmoid, Tanh, exponential, softmax are some of the activation functions built into Keras. ReLU is generally preferred in the mid-layers of a neural network. The ReLU activation function returns 0 if the input is less than 0 and returns x if the input is greater than 0. The first and second Dense layers are controlled by the ReLu function. Categorical Cross Entropy is used as the loss function when the classification is one-hot encoded.

Results

From the confusion matrix in Table 1, it is detected that the FN, FP and TN rates are null for all the classes stating the Accuracy, Precision, Recall and F1 Score to be greater than 99%.

	Healthy	Unhealthy
Healthy	16	0
Unhealthy	0	20

Table 1: Results in confusion matrix for the test dataset

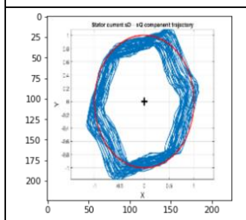
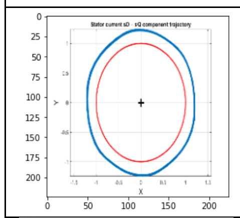
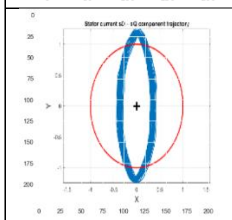
Park Vector	True Values	Prediction
	Healthy	Healthy
	Healthy	Healthy
	UnHealthy	UnHealthy

Table 2: Testing Predictions

Testing Predictions derived from the confusion matrix are shown visually are shown in Table 2 with specific True Values and Prediction Columns.

Conclusion/ Summary

In the proposed work, ANN model for the various bearing fault segregation classification has been developed based on Park’s vector analysis of three-phase stator currents. The experimental results indicate that the developed ANN model renders >99% classification results for the datasetFurther, the proposed and designed model is compatible with Linux OS and can thus be deployed in a RaspberryPi (RPI), the preferred edge device in most industries for industrial automation. The deployed model has proved to be robust and stable and has outperformed the accuracy of the existing predictive maintenance models. The usage of RPI enables the industry to conduct predictive maintenance at a low-cost factor and a minuscule energy footprint, thus enabling enterprises to reduce full-scale maintenance and run the plants smoothly and effectively.

Contact Details

aadhi0610@gmail.com, valli.meenaa9@gmail.com

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