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COMPARISON OF MACHINE LEARNING METHODS IN PREDICTIVE MAINTENANCE APPLICATIONS OF ELECTRIC MOTORS

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Abstract – Three-phase asynchronous motors are widely used in many areas of industry. Unplanned malfunctions in the motor can cause the entire system to become inefficient. Detecting and intervening the malfunctions before they grow has a direct impact on the life of the motor and contributes positively to the operating economy. Therefore, it is important to detect motor failures in advance and perform predictive maintenance. In this study, the vibration data of a three-phase asynchronous motor of Volt Electric Motors under full load was measured with a motion sensor. The created data set was analyzed by processing with Polynomial Regression, Spectral Analysis, ARIMA and Artificial Neural Network models. An attempt was made to predict future data. The artificial Neural Network model gave the most effective result among these models. First, classes were created with the health data of the motor and the corrupted versions of this data at certain rates. Then, the model was established and the training was carried out. The model classified the test data with 96% accuracy. By looking at this classification, it has been concluded that it can be determined whether the motor is defective or not. Four different methods were analyzed and the results were shared.

Keywords – Electric Motor, Predictive Maintenance, Artificial Intelligence, Machine Learning, Artificial Neural Network

I. INTRODUCTION

This project has been developed to detect the malfunctions that may occur in the electric motors used in the production facilities before the malfunction occurs and take the necessary precautions.

Today, electric motors are widely used in industry and production lines. Any malfunctions that may occur in these engines create serious interruptions in production and bring serious financial losses depending on the size of the malfunction. If these faults can be detected before they occur or when they are just beginning to occur, losses that may occur due to faults can be prevented [1].

Today, there are three different maintenance and repair strategies. Corrective maintenance means performing a diagnostic work on a machine that has already broken down, and taking action to eliminate this malfunction after the cause of the malfunction is determined. Preventive maintenance, on the other hand, unlike corrective maintenance, is performed before the malfunction occurs. Preventive maintenance should be timed very well. Periodic preventive maintenance performed early and at frequent intervals can be very costly. The reason for this is that the equipment that has not expired is replaced while it is intact [2].

Detecting damage beforehand and taking action is called predictive maintenance. In predictive maintenance, after the physical data collected from the machines by various methods are processed, it can be determined with a high accuracy when the malfunction may occur.

At this point, the high processing power capability of the machines can be used. Machine learning algorithms can be used. These algorithms, which can make predictions, are widely used in prediction systems today. It is expected to make inferences by training these algorithms about the subject or situation on which it will make predictions with the data we have.

In this project, we aim to teach the model the differences in the vibration of an engine in non-failure and malfunctioning situations and to make accurate predictions and interpretations about the data sets that we will give later. During the project, various machine learning algorithms and statistical approach models were tested on the data set and compared to determine the most successful one.

Machine learning is a subgroup of artificial intelligence approaches. In general, it is the process by which a system acquires and integrates information through large-scale observations and develops itself by learning new information rather than being programmed with that information. Unlike traditional programming, the method is a program and does not require input from us. Instead, it creates a program by taking input and output.

II. MATERIALS AND METHODS

The data set we have consists of values taken from a vibration sensor. This sensor records one thousand six hundred pieces of data for x, y and z every second. This shows that we have a fairly large data set. In this study, Polynomial

Regression, Spectral Analysis, ARIMA and Sequential models were tested for the data set we have, respectively.

A. Polynomial Regression

The polynomial regression model makes predictions on this equation by subtracting an equation from the data given to it. Although this model was very successful in making predictions, it was not successful in making predictions as seen in Figure 1.

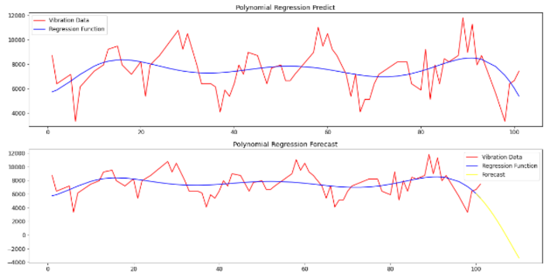

Figure 1

B. Spectral Analysis

Spectrum analysis reveals the sources of interference by showing the spectral components. The time domain provides useful information about the signal, such as pulse rise and fall times. In the spectral analysis model used on Python in this study, the prediction results looked promising at first. However, when the time interval was extended, it was noticed that the model repeated the previous data and did not make any predictions.

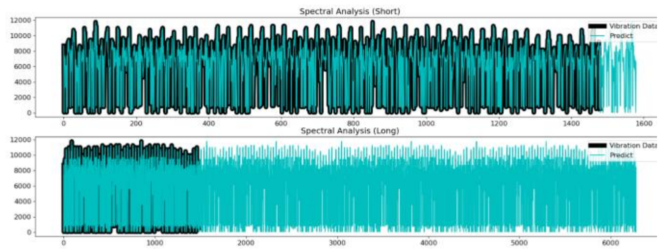

Figure 2

C. ARIMA Model

The purpose of the ARIMA (Autoregressive Integrated Moving Average) model is to predict the future value of the variable from the past values of the series and the prediction errors made in the past. It consists of three parts: AR (autoregressive), I (integrated), and MA (moving average). The parameters that represent these in the model are p, d, and q parameters, respectively [3].

1. AR (p): It expresses the degree of relationship between the current data and historical values of the model.

2. I (d): If our data set is not stationary, it allows us to make our data set stationary.

3. MA (q): Builds the model as a linear combination of past mistakes.

In this model, firstly, the ADF (Augmented Dickey-Fuller) test is applied to examine whether the data set is stationary. Since the p-value in this test is greater than 0.05, it is concluded that the data are not stationary and a first-order difference should be taken to make them stationary (d = 1). Then, by examining both the grid method and the ACF and PACF graphs, the appropriate p and q values are found. Whether these parameters are statistically significant or not is checked by looking at the p-values after establishing the model. Finally, the residuals should be checked for autocorrelation using the Durbin-Watson statistics.

This model gives a very successful result in estimating the near time values, as seen in figure 3.

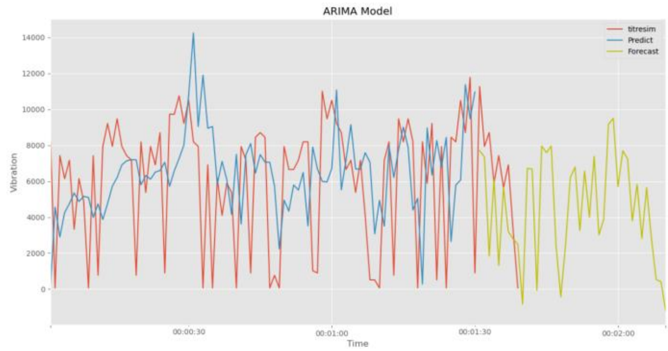

Figure 3

However, as seen in Figure 4, when we expand the time interval we want to predict, the model starts to repeat with the previous values.

Figure 4

D. Sequential Model

This model belongs to the deep learning category of machine learning.

The difference between deep learning and machine learning can be explained as follows. Machine learning learns models and draws a conclusion. However, if the result is not successful, it needs to be retrained. Deep learning models, on the other hand, don't work that way. Deep learning algorithms learn a data set and can learn from the mistakes it makes while learning with the back propagation technique. It does not require any human intervention.

Its logic is based on artificial neural networks. Artificial neural networks imitate the structure of human biological neural networks, and their remembering and learning abilities. It consists of layers and neurons. Here, the higher the number of layers and neurons, the higher the learning ability, but since the model stops learning after a certain point and begins to memorize, we need to keep the number of them at the optimal level. We follow this memorization situation from the epochs graph seen in figure 3.

The model is imported from Python's tensorflow library. Tensorflow is an open source library focused on training neural networks.

Before starting the training, the data set consists of healthy data and artificially added noise at certain rates. The reason for this is to teach both healthy and damaged data to our model without the need to break the engine. In this way, the model can classify healthy and damaged data. Then this data set is divided into training and testing and the model is trained.

After the data set is prepared, the model starts to be trained in parts. Each of these training pieces is called an epoch [4].

The model consists of eight hidden layers and one hundred fifty-five neurons. There are four outputs in the output layer. This is because there are four degrees of damage.

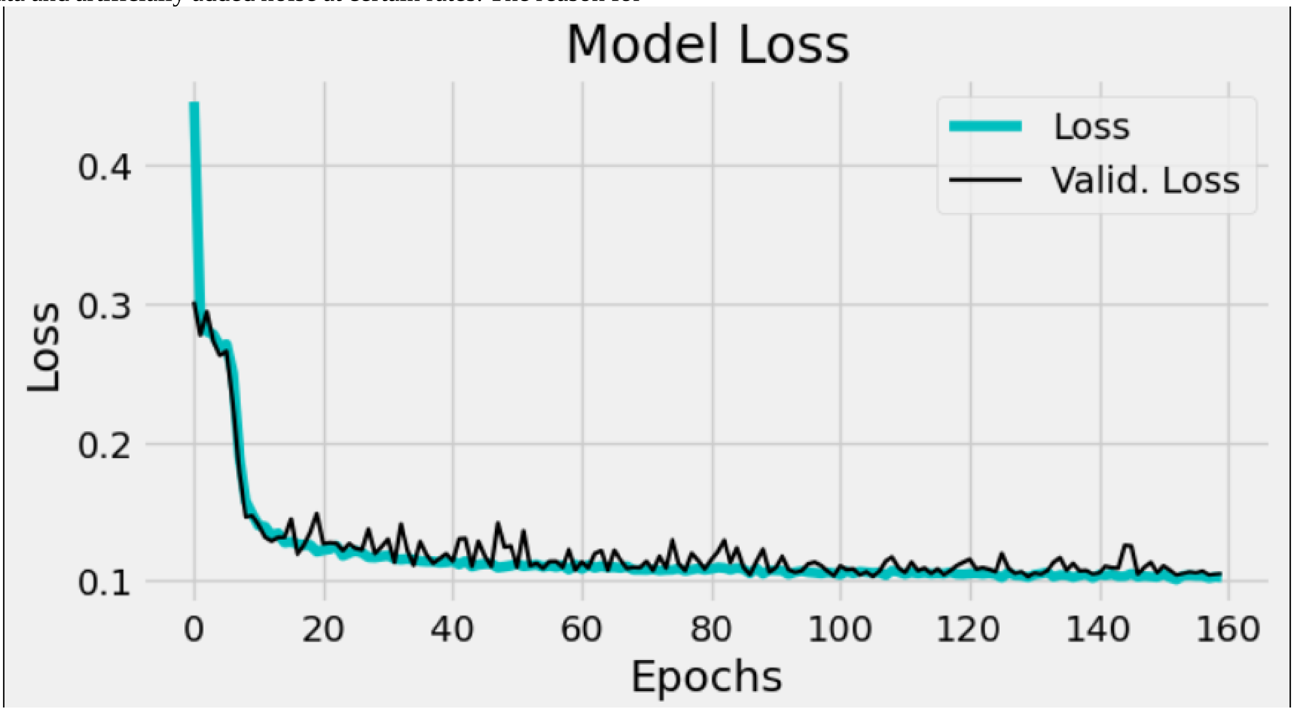

Figure 5

While creating this model, the hyperbolic tangent (tanh) activation function was used for neurons. Our activation function model must learn from its mistakes with the backpropagation technique. In the output layer, the softmax activation function is used.

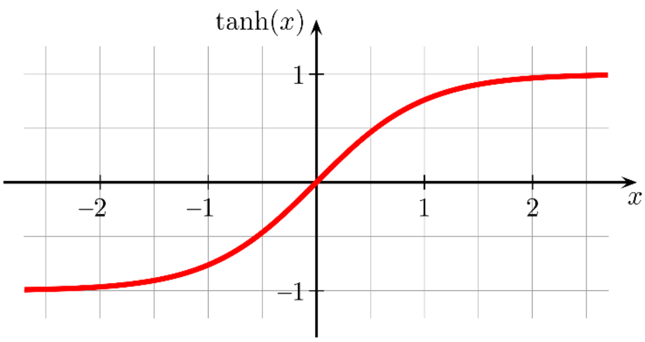

Figure 6

III. Results

The model provided a 96% accuracy rate on the test data. Then, one damaged and one undamaged engine data were given to the model that it had never been trained before. The results are as in Table 1.

Table 1

Healthy Motor	
0	79782
1	0
2	0
3	218

Table 2

Damaged Motor	
0	68539
1	133
2	1803
3	9525

As can be seen in Table 1, the model can distinguish between healthy and damaged engine data.

It has been determined by FFT Analysis that the third-order mesh signals in the healthy motor data here are noise.

IV. DISCUSSION

The use of this maintenance method for fault detection of motors is of great importance in terms of production and cost losses. The most important feature that distinguishes the model from its counterparts is that it produces it artificially by not needing corrupted engine data in the study.

V. CONCLUSION

As a result of the studies, even if the failure situation cannot be determined beforehand, it can be inferred about the life of the engine by determining the percentage of damage by classifying the damage situation of the engine at that time.

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