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Application of Deep Learning in Predictive Maintenance of Rotating Machinery

Akhil Sivanand[1], Regi Kumar V[2]
[1]*Student, Department of Mechanical Engineering, College of Engineering, Thiruvananthapuram, India*
[2]*Professor, Department of Mechanical Engineering, College of Engineering, Thiruvananthapuram, India*

***Abstract*— In today's competitive industrial world, predictive maintenance is having extreme importance. With early prediction, timely maintenance can be done and long time working of machinery can be assured. Predictive maintenance involves collecting condition monitoring data such as vibration measurements, thermal data and ultrasonic emissions and analyzing them to predict any failure in future. This allows the maintenance engineers to effectively make timely action. The integration of deep learning in predictive maintenance has proven to be effective through years of research and this is focused in this work.**

This paper discusses different maintenance management techniques including predictive maintenance in detail. The paper further discusses a real case study on predictive maintenance system created for a single-phase electric induction motor. An experimental setup for single-phase electric motor was made using internet of things (IoT) components. The data from the IoT devices which involve vibration and temperature measurements were collected until failure of the system. This data was then processed and analyzed using Microsoft excel and python. Finally, the Remaining Useful Life (RUL) was predicted using a deep Recurrent Neural Network (RNN) and the performances were evaluated.

Index Terms—Internet of Things, Preventive maintenance, Artificial Intelligence, Predictive Maintenance system, Remaining Useful Life.

I. Introduction

Maintenance is considered as an import activity in any industry. Maintenance costs cover about 60 to 70% when manufacturing costs in an industry are considered. Cost of replacing these components can be really high. Even though this is the scenario, it is often neglected and the maintenance techniques currently used does not consider the real condition of the machine tools and equipment. Failures can often come as a surprise and can bottleneck the system and can result in several wastes like defects, delays etc. Manufacturing systems have now advanced in technology and often use monitoring techniques for maintenance purposes to identify failures by analyzing the current health of machinery, but even today, the maintenance solutions and monitoring techniques are not completely linked.

In most plants, reported maintenance costs include many non-maintenance related expenditures. These maintenances are beneficial only in a short term. The expenditure spend for core maintenance activities is much less. The failure costs associated with complex machinery can be very high. Hence, these costs are significant when considering the productivity of a firm.

II. Literature Review

In general, maintenance management techniques are categorized into (a) Run-to-Failure Management, (b) Preventive Maintenance and (c) Predictive Maintenance Management.

In Run to Failure Management, maintenance is done only when the machine breaks down. There are hence no costs associated with maintenance in this type of management system. It is employed generally when the repair costs associated with failure are relatively less. It is also called "no maintenance" approach of management. This practice is followed by very few number of industries. Here there can be several expenses such as those associated with inventory cost, high overtime labour costs, high machine downtime, and low production availability.

Preventive Maintenance is time driven type of maintenance, where the maintenance procedures are dependent on time. From the mean-time-to-failure (MTTF) or bathtub curve, it is evident that the probability of failure of a new machine during the first few weeks after installation is very high. After this initial period, the chances of machine failure decrease relatively. After a few more weeks of operation, the chances of failure increases. In preventive maintenance management, MTTF statistic are used to determine when maintenance procedures need to be done. In preventive maintenance programs repairs, lubrication, adjustments, and machine rebuilds are carried out based on the condition of the machinery. Here the assumption is that all machines fail after a particular period. Even though preventive maintenance is better than run to failure maintenance, abrupt changes in working of machinery can cause unpredicted failures.

Predictive maintenance is regular monitoring of the actual mechanical condition, operating efficiency, and other indicators are carried out and these measurements are used to predict the failure of a machine in future. Predictive maintenance can improve productivity, product quality, and overall effectiveness an industry by accurately spotting the failures and hence reducing huge failure costs. Predictive maintenance can be defined as a technique, which uses the actual operating condition of plant equipment and systems to optimize total plant operation by predicting equipment failure

Predictive maintenance does not rely on recorded lifetime values but uses real time maintenance data to predict the failure of equipment.

In preventive maintenance, the final decision can be taken only after consultation with an expert, whereas in predictive maintenance expert opinion is not required and the intelligent systems can accurately predict when the repairs need to be carried out. The predictive maintenance system will provide factual data on the actual mechanical condition of each machine. A predictive maintenance program can minimize breakdowns and make sure that the machines are always in proper working condition. The mechanical problems don't become serious if they are detected and repaired early. Here predictive maintenance based on temperature and vibration is carried out. Vibration frequency components of failure can be easily identified and amplitude of each distinct vibration component will remain constant when a particular failure is induced. These parameters are most important in vibration analysis. Other condition monitoring techniques are process parameter monitoring, thermography, ultrasonic emission analysis, and acoustic emission analysis. Each technique has different types of datasets and the processing and analysis varies on different processes. Here maintenance is done only when the machine breaks down. There are hence no costs associated with maintenance in this type of management system. It is employed generally when the repair costs associated with failure are relatively less. It is also called "no maintenance" approach of management. This practice is followed by very few number of industries. Here there can be several expenses such as those associated with inventory cost, high overtime labour costs, high machine downtime, and low production availability.

A. Deep learning and Internet of Things (IoT)

Developing a predictive maintenance system requires massive amount of data. This data is often messy and filled with noise. So first this data should be processed so that it can be fed to the neural network. The first step in data processing is data cleaning. This is an important step because data can contain a lot of noise when collected using a sensor or errors when the data is manually entered. Data cleaning ensures that error-free data only is used for further analysis (Jardine et al., 2006). For condition monitoring data, data errors may be caused by sensor faults, noise in the background or by manual errors. In such cases, isolation of the sensor is the right way to eliminate any occurrence of errors. In general, however, data cleaning is no easy task. This require complex coding and might take a lot of time than actually anticipated. Data processing for waveform and multidimensional data can also be called signal pro-cessing. A variety of signal processing techniques have been developed and discussed in precious works in order to analyse such data so as to provide useful information in diagnostic and prognostic uses. This can include prediction, categorisation, identification, etc. (Leone et al., 2017) used an approach based on statistical similarity of data to predict remaining useful life (RUL) of circuit breakers. The proposed algorithm had very high prognostic power or ability to calculate RUL effectively. In order to extract useful information from raw signals we use a technique called feature extraction. The features required for training an artificial neural network are often obtained in noise filled condition. This problem was addressed by (Lin et al., 2018) by using an auto encoder to convert the raw signals to information rich features. Signal processing for multidimensional data such as image data is more complicated and usually require advanced tools for this purpose. However, there is much less studies on application of image processing techniques in industries. (Jardine et al., 2006)

(E. Marchi and Schuller, 2017) used deep recurrent neural network based autoencoders for acoustic novelty detection. He used acoustic signals to build a regression model. He suggested that acoustic signals use comparatively less computational costs.

The Internet of Things (IoT) is the network of devices which enables these objects to connect and exchange data, where the components or things have unique identities. Each of these things is uniquely identifiable and is able to inter-operate within the existing Internet infrastructure. IOT connects anything and anyone at any time and any place through its constant connectivity. IoT can also be called Internet enhanced by sensors. When the sensors are attached to the Internet, they can source data and control actuation. The sensors include hardware sensors and sensor networks. Along with that, they software sensors and can be used to capture a variety of data. Sensor technology has made huge progress recently and now can be used as reliable source of data.

IoT is maintained with the help of microprocessors like Arduino, Raspberry Pi etc. Arduino can be used to create interactive objects, it can be used to read data from a great variety of switches and sensors, and control different kind of lights, motors and other types of physical actuators. Arduino projects can be made autonomous and they can also interact with other software running on a computer. SB connection or with an external power supply, like a rechargeable or non-rechargeable battery. In similar works other type of microprocessors are also used. (Ambrož, 2017) used a raspberry pi as data acquisition system for collecting data from a bicycle and (Orhan et al., 2016) used CSI 2110 machinery analyzer for vibration measurement and analysis.

B. Induction motor faults

The most common failures that occur in an induction motor are bearing faults, stator winding faults and rotor faults.

The rotor is supported at two ends by means of bearings attached at the two ends. Each bearing has races and rolling elements called balls to facilitate rotation. Inner race is attached to shaft and results in power transfer. Friction between races and balls can be reduced by using proper lubricants. Faults occurring in these races or the balls can be called bearing defects. In terms of induction motor failure statistics, bearing failures are the most frequently fount defects in most induction motor faults. According to the study of EPRI 41 to 42% of induction motor faults are due to bearing failure.

Stator winding faults generally occur due to failure of insulation. This fault occurs due to short circuit between different components of the rotor. Physical and environmental effects can contribute to the occurrence of this kind of defects. Stator winding failure can occur due to mechanical stresses between stator and rotor, environmental stresses such as humidity and temperature and electrical stresses occurring due to variations in voltage. Among these causes, thermal stresses are the highest contributing factor in stator winding faults.

Rotor faults results from broken bars, broke end rings and misalignment of the rotor. Rotor failures due to asymmetry is most common in squirrel cage induction motor. Heavy end rings can also contribute to imbalances in rotor. These kinds of asymmetries can contribute to large cracks in the future. If one of the bars breaks, the side bars will carry higher currents and mechanical stresses and eventually side bars may also get cracked, spreading the damage. This can result in multiple cracks and can spread to various locations of the rotor.

III. Methodology

The methodology involves literature study, platform and tool selection, data collection, data analysis, model building and evaluation of results. The data was collected from a single-phase motor using an Arduino Uno microprocessor. Temperature and vibration data was collected using the sensors attached to the microprocessor. Later these datasets were uploaded into Python IDE. Then the data was cleaned and labelled. Finally, a deep recurrent neural network-based model was created to predict the remaining useful life of the motor. The main libraries used are Scikit-learn, matplotlib, Numpy, pandas, keras,LSTM and tensor flow.

IV. Experimental Setup

The experiment was conducted on a single-phase AC motor manufactured by Beetex Industries. The experimental setup consisted of temperature probe model DS18B20 and accelerometer model ADXL335 connected to Arduino UNO microprocessor. Arduino can be called a mini computer with an open code. It is based on a board with a simple microcontroller and a programming environment to control the data collection, processing and actuation. A picture of the Arduino UNO microprocessor used in the experiment is shown in the Fig. 1.

Fig. 1. Arduino Uno

The sensors were connected to the Arduino microprocessor by means of connecting wires and bread board. The measurements were collected and stored on Cumulocity, which is a popular IOT platform. Datasets required for the work were created automatically by Cumulocity.

V. Data Collection

The experiment was done on an induction motor extracted from a conventional mica grinder used for domestic applications. The photograph and specifications of the Induction motor used for the experiment is given below.

TABLE I
Units for Magnetic Properties

Rated Voltage	230 V
Input Frequency	50 Hz
Phase	Single Phase
HP	0.25
Full Load speed	1440 rpm

Fig. 2. Single phase motor selected for experiment

Fig. 3. Experimental setup

The thermal data was collected using DS18B20 temperature probe and vibrational data was collected using ADXL335 accelerometer. The data was recorded and saved using Cumulocity IOT platform. In a similar work (Dong et al., 2017) used an IOT based predictive maintenance system for efficient monitoring of a coal mine system. Cumulocity works with any network architecture but is specifically designed to work out of the box with mobile networks. It's inbuilt support for Arduino and network connectivity enabled a faster set up of the data acquisition system. Visualisation of data and conversion of data into csv format was supported in the application. The data was collected until failure and was written in csv format for further analysis.

VI. Remaining Useful Life Prediction

The motors are important components of the majority of the industrial production processes. Therefore, these machines are extremely important in increasing the overall reliability of the production process. Hence many techniques have been developed for an on-line motor monitoring of the behavior and performance. Usually condition monitoring techniques which involve preventive maintenance are applied on induction motors which involve monitoring the health of the machinery during the course of all its useful life. Unlike a preventive system, the aim of a predictive maintenance system is to recognize the development of failures in an initial state. Each failure must be detected as soon as possible in order to promote programmed stop of the machine. The extracted data sets contained vibration in 3 axis and temperature measurements in Celsius scale.

TABLE II
Data Review

ID	X Acceleration	Y Acceleration	Z Acceleration	Temperature
1	0.591	-1.161	0.436	37.13
1	-0.664	-1.657	1.124	37.13
1	0.137	0.082	-0.569	37.19
1	-0.513	0.476	0.31	37.19
1	0.309	1.452	-1.683	37.19
1	-0.215	1.389	-0.185	37.19
1	0.935	0.968	-0.163	37.19
1	-0.397	-1.094	0.331	37.19
1	0.471	-1.12	0.373	37.25
1	-0.457	-1.688	1.556	37.25
1	-0.049	-0.572	-0.795	37.25
1	-0.431	0.28	0.648	37.31
1	-0.007	1.216	-1.366	37.31
1	-0.155	1.552	-0.637	37.31
1	0.625	1.218	-0.158	37.31
1	-0.065	-0.616	0.265	37.31
1	0.215	-1.085	0.153	37.38
1	-0.105	-1.56	1.708	37.38
1	-0.241	-1.192	-0.411	37.63
1	-0.334	0.104	0.57	37.63

VII. Data Pre-processing

Data cleaning of the collected measurements were required due to the presence of massive amount of data and possible interferences during data collection. Cleaning ensures that error-free data only is used for further analysis (Jardine et al., 2006). This is an important step because data can contain a lot of noise when collected using a sensor or errors when the data is manually entered. Data cleaning ensures that error-free data only is used for further analysis (Jardine et al., 2006). For condition monitoring data, data errors may be caused by sensor faults or noise in the background. In such cases, isolation of the sensor is the right way to eliminate any occurrence of error. The next step of data processing is data analysis. A wide variety of models, algorithms and tools are available in to accurately analyze the data to make it more understandable. The selection of models, algorithms and tools used for data analysis depend mainly on the types of data collected. Data processing for waveform and multidimensional data can also be called signal processing. A variety of signal processing techniques have been developed to analyse a such data in order to provide useful information diagnostic and prognostic purpose, which can include prediction, categorization, identification, etc. (Leone et al., 2017) used a data driven approach based on statistical similarity to accurately predict remaining useful lie of circuit breakers. The proposed novel algorithm showed very high prognostic power. In order to extract useful information from raw signals we use a technique called feature extraction. He features required for training an artificial neural network are often obtained in noise filled condition.

VIII. Development and Implementation

Python 3.6 is used in this work and Spyder along with anaconda was used as the IDE. Scikit-learn, pandas, NumPy, keras, tensor flow etc were used for developing the deep framework of the model. NumPy and pandas were used for data pre-processing, keras and TensorFlow were used for training and testing the model and finally matplotlib library of python 3.6 was used for plotting the graphs.

The datasets, which were available in multiple csv files, were combined with the help of windows command prompt. To make data ready for building a machine learning algorithm, data pre-processing was carried out, which involved labelling and arranging the data frame to be given as input to the neural network to convert the data into the desired format. Since vibration parameters are not normalised, they should be converted to normalized data, which is done as part of data pre-processing step, an action commonly known as feature scaling. The collected measurement data from each sensor are normalized to be within the range of negative 1 and positive 1 using the min-max normalization method. As the final step of data pre-processing, the test set and training set are defined and input and output parameters are labelled accordingly. In contrary to common regression problems, the desired output value of the input data is difficult to determine for a remaining useful life prediction problem. That is because in many industrial applications, it is impossible to evaluate the precise health condition and estimate the RUL of the system at each time step without an accurate physics-based model. For this model, a linear degradation model has been validated to be suitable and effective in determining the remaining useful life.

IX. Model Building

Temperature measurements were merged to the vertical displacement row. The model was split into input and output layers. Then the model was defined and different components like input layer, input shape, hidden layers and output layer are added to the neural networks. . The batch size was fixed as 100 and number of epochs was fixed at 50 based on convergence. The training of the model was done on a Nvidia gt 940m graphic processing unit and took 5 hours for the process to finish. The model was trained using Recurrent Neural networks

A. The LSTM layers

The LSTM(Long Short Term Memory) layer is used in this model to deal with the sequential nature of data. A recurrent neural network can be called a neural network, where the activation of a neuron is fed back to itself. The RNNs however lack the ability to learn from long term dependencies. This problem was addressed with the introduction of LSTM networks. An LSTM layer offers a richer internal state by using a cell state in addition to the hidden state and various gates.

B. Dropout

Dropout is often used to reduce data overfitting when training a neural network especially when the available dataset I small in size. Overfitting of training dataset often results in an excellent performance on training dataset and poor performance on test dataset. Dropout prevents this by complex co-adaptations on the training data and avoiding the extraction of same features repeatedly. Dropout is realized by setting some hidden neurons to zero so that the neurons are not included in the forward propagation training process. However, dropout is turned off while testing so that all neurons are involved in predicting the output.

X. Training and Validation

Mean squared error was the metrics used in training the mode and the trained model was validated by predicting the remaining useful life of the test data and comparing it with the actual RUL.

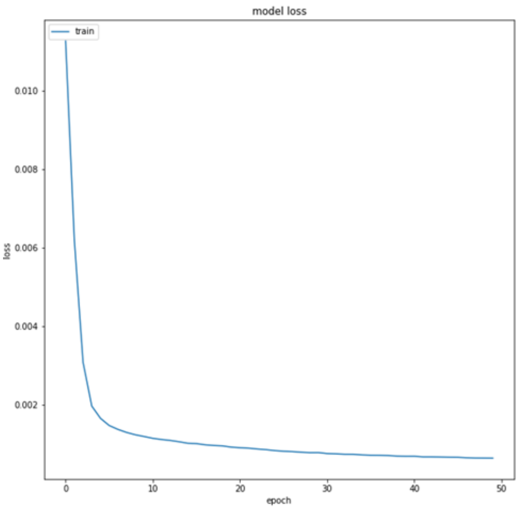

Fig. 5. History of model loss

The predicted and actual data was compared using an x-y graph made using the matplotlib library.

XI. Results and Discussion

An experimental setup was created to collect real time data and data was collected with the help of an Arduino board coupled with an ADCL335 and DS18B20 temperature probe. The IoT devices were able to collect real time data accurately and this data was fed into a recurrent neural network to predict Remaining Useful Life (RUL).

TABLE III
Results Predicted by RNN

z	temp	cycle	rul	predicted
-0.046	37.69	50	69061	67644
-1.135	37.69	51	69060	67694
1.745	37.75	52	69059	67735
-1.034	37.75	53	69058	67894
-0.364	37.75	54	69057	67530
0.349	37.75	55	69056	67646
-0.001	37.75	56	69055	67794
-0.33	37.75	57	69054	67721
-1.378	37.75	58	69053	67717
1.66	37.75	59	69052	67786
-0.794	37.75	60	69051	67933
-0.593	37.75	61	69050	67543
0.605	37.75	62	69049	67655
0.166	37.75	63	69048	67832
1.295	37.75	64	69047	67708
-1.634	37.75	65	69046	67754
1.388	37.75	66	69045	67669
-0.346	37.75	67	69044	67697
-0.794	37.75	68	69043	67426
0.585	37.75	69	69042	67440
0.075	37.75	70	69041	67585

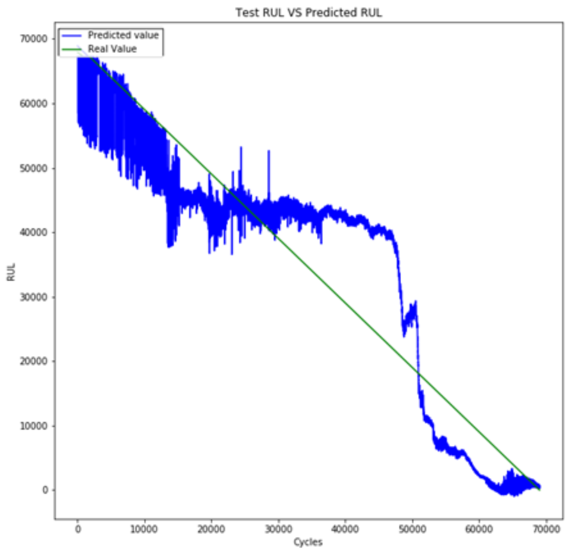

Fig. 6. Real vs. Predicted RUL

The model was able to predict the vibrations with a mean squared error less than 0.0002. From the plotted graph it can be seen that the predicted vibration can be taken as a reliable measure for predicting the breakdown of induction motors and hence can be used for creating a reliable predictive maintenance system.

XII. Conclusion

In this work, a LSTM based deep neural network was used for prognostics in an induction motor. Dropout technique is employed to relieve overfitting problem. Experiments are carried out on manually collected data to make this work a holistic approach. The goal of the task is to estimate the remaining useful life of the motor accurately. With raw feature selection, data pre-processing and sample preparation using time window, good prognostic performance was achieved using the proposed method, and very small error between the prediction and the actual RUL value is obtained for the testing data. This ensures that the RUL in the life-time of the motor units can be well predicted. The effects of the number of hidden layers and time window size on the prognostic performance are investigated and fine-tuned for better performance. Considering the estimation accuracy and computational ability for the training process and the dataset information, the number of input layer was fixed as 200 and number of hidden layers was fixed as 100. The size of the time series was fixed as 100. It can be understood that the proposed network has shown its superiority on the prognostic accuracy and is promising for industrial applications. Additionally, it should be noted that the data pre-processing method called min-max normalization is used in this study, since normalized data facilitate the network training process. The current training time is longer than most other networks in the literature, this can be addressed in the future works. More datasets which include ultrasonic waves, acoustic emission, thermographic data etc. can be used to make a more accurate predictive maintenance system. Deep learning methods generally suffer from high computing load, and that should be focused on in further research.A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

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