International Journal of Advanced Engineering, Management and Science (IJAEMS)
Peer-Reviewed Journal
ISSN: 2454-1311 | Vol-8, Issue-5; May, 2022
Journal Home Page: https://ijaems.com/
Article DOI: https://dx.doi.org/10.22161/ijaems.85.1

Study on Predictive Maintenance for Controller Failure

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Received: 09 Apr 2022; Received in revised form: 02 May 2022; Accepted: 09 May 2022; Available online: 14 May 2022

Abstract**—***It is more important to be able to predict a failure before it occurs than to fix it after a failure. Attempts to predictive maintenance beyond reactive maintenance and preventive maintenance are increasing. This paper contains basic research to design a system that can predict controller failure before it occurs. The database related to the controller should be designed considering not only the data of the controller itself, but also the information on the operating environment, and the processing contents in the failure situation. In the latter part of the paper, data classification and analysis algorithms that can be used for failure prediction are summarized.*

Keywords**—*****Predictive maintenance, Failure Prediction, Maintenance, AI.***

I. INTRODUCTION

The controller inevitably suffers damage due to external impact, wear, crack, etc. or degradation during operation, and such management incurs a large operating cost. It is very difficult to detect in advance a fatal accident that exceeds the limit level or a case of discontinuation of use with existing preventive activities. Currently, damage costs are incurred due to system downtime by relying on corrective maintenance to repair when a failure occurs. And since the current preventive activity actually depends on regular maintenance, maintenance is performed unconditionally regardless of the actual defect, and high costs are incurred due to frequent system downtime and replacement of parts due to appearance.

This paper is a basic research step to build a system that can predict a controller failure situation before it occurs. Then, we learn about predictive maintenance, and look at data organization and AI algorithms to design this system. Based on these contents, we plan to materialize a model that can be commonly applied to various controllers so that the controller can predict the current situation and future failure events by itself.

II. PREDICTIVE MAINTENANCE

Most of domestic maintenance is reactive maintenance, followed by preventive maintenance, and predictive maintenance using statistical techniques and AI is increasing recently.

Predictive maintenance is a method of preventing asset failure by analyzing production data to identify patterns and predict issues before they happen [1]. The key to this is a combination of big data analytics and artificial intelligence in order to create insights and detect patterns and anomalies. It includes continuous real-time monitoring of assets in combination with external data (e.g. environmental data, usage, etc.) with alerts based on predictive techniques such as regression analysis. The basic components of predictive maintenance in the context of industry 4.0 are: Sensors, Cyber-Physical Systems, Internet of Things, Big Data, Cloud computing, Networks and Artificial Intelligence, Mobile networks, WIFI[2].

Predictive maintenance is a data science technology that creates a predictive model by collecting a lot of data related to managed equipment. It does not predict equipment failure with just one or two signs, but quantifies and models numerous symptoms and historical data of actual failure. Of course, the more data, the more accurate it is also increases.

Table. 1: Comparison of Maintenance

	Reactive Maintenance	Preventive Maintenance	Predictive Maintenance
Advantage	• low cost • low human power	• Flexible adjustment of maintenance timing • Increase the lifecycle of components • Cost reduction compared to reactive maintenance	• Improving the operating life/availability of components • Dramatically reduce equipment or process downtime • Reduced parts and labor costs • Expect a lot of cost savings compared to reactive maintenance
Disadvantage	• Unplanned downtime of equipment or equipment • Increased labor costs • Equipment repair or replacement costs • Huge loss of revenue due to equipment failure • Occurrence of inefficient use of human resources	• Unplanned downtime of equipment • Unnecessary maintenance • Labor-intensive work	• Increased investment in diagnostic equipment • Increased investment in employee training

Table. 1: Correlation of Industrial Revolution and Maintenance [3]

Industry revolution	Industry 1.0	Industry 2.0	Industry 3.0	Industry 4.0
Characteristics of the industrial revolution	Mechanization, steam power, weaving loom	Mass production, assembly lines, electrical energy	Automation, computers, electronics	Cyber Physical Systems, IoT, networks, cloud, BDA
Type of maintenance	Reactive maintenance	Planned maintenance	Productive maintenance	Predictive maintenance
Inspection	Visual inspection	Instrumental inspection	Sensor monitoring	Predictive analysis
OEE	<50%	50-75%	75-90%	>90%
Maintenance team reinforcement	Trained craftsmen	Inspectors	Reliability engineers	Data scientists

Advanced predictive maintenance can make equipment maintenance extremely efficient. Regardless of the condition of equipment, it is possible to break away from the existing method of maintenance as planned, to repair equipment with a high possibility of actual failure first, and to prevent excessive maintenance such as replacement of unnecessary parts. In particular, predictive maintenance includes not only cutting-edge digital technologies such as AI and machine learning, but also industry-specific experts such as equipment, process, and chemistry to design, so it is possible to make more sophisticated predictions by incorporating the practical needs of industrial sites.

III. STEPS FOR FAILURE PREDICTION

1. Data Preprocessing

Data preprocessing consists of following steps.

① Reading data: read raw datasets.

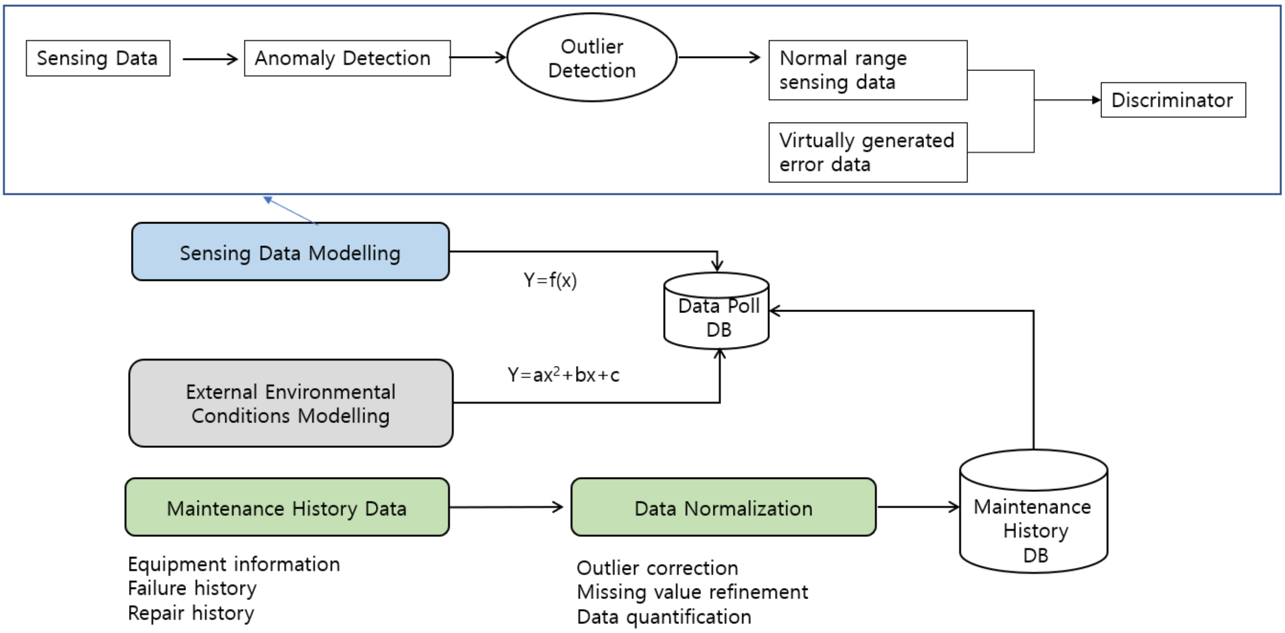
② Checking the data: check for missing values, categorical data, and convert data if it is needed.

③ Standardizing the data: standardize data if it is needed.

④ Splitting the data: split data into train and test set.

2. Making data poll

Before training, making data poll databases is important.



Device Type	Serial Number	Temperature	Humidity	Check Date	Check Result	Repair Data	Predictive date

Fig. 1: Data Poll DB

3. Modelling for predictive maintenance

As the result of study, models for the predictive maintenance are as follows.

3.1 Random Forest

A random forest (RF) classifier is an ensemble classifier that produces multiple decision trees, using a randomly selected subset of training samples and variables. This classifier has become popular within the remote sensing community due to the accuracy of its classifications [4].

The computing time required to establish the RF classification model is:

$$T\sqrt{MNlog(N)} \qquad (1)$$

where T is the number of trees, M is the number of variables used in each split, and N is the number of training samples [5].

3.2 Logistic Regression

The logistic regression model predicts logit values for each case as linear combinations of the independent variable values. A predicted logit for case i is obtained from the solved logistic regression equation by substituting the case's values of the independent variables into the sample estimate of the logistics regression equation[6],

$$logit_i = b_0 + b_1x_{i1} + b_2x_{i2} + \ldots + b_mx_{ik} \quad (2)$$

The predicted probability for case i is then given by

$$p_i = \exp(logit_i) / [1 + \exp(logit_i)] \qquad (3)$$

3.3 Gradient Boosting

The Gradient Boosting algorithm is an algorithm that boosts using gradients. Boosting is the process of creating a strong classifier by combining weak classifiers. This process is performed sequentially by adding them one by one. If we continue this way, the residuals will continue to shrink, and we will be able to build predictive models that describe the training set well. However, this method can significantly reduce bias, but has the disadvantage of overfitting.

3.4 XGBoost

XGBoost(Extreme Gradient Boosting)is a scalable machine learning system for tree boosting, which is available as an open source package [7]. The algorithm implemented using the boosting technique is representative of Gradient Boost, and the library that implements this algorithm to support parallel learning is XGBoost.

It supports both regression and classification problems, and it is a popular algorithm because of its good performance and resource efficiency.Here, boosting is one of the ensemble techniques that uses a combination of several low-performance models.A strong prediction model is created by weighting the training errors of low-performance prediction models and sequentially reflecting them on the next training model.

Advantages of XGBoost are as follows.

- Faster execution time compared to the existing boosting model (parallel processing)
- Support for over-conformance regulation (Regularization)
- High predictive performance in classification and regression tasks
- Early Stopping feature provided.
- Customizing is easy by providing various options.
- Handles missing values internally.

3.5 K Nearest Neighbors

kNN classifier is to classify unlabeled observations by assigning them to the class of the most similar labeled examples. Characteristics of observations are collected for both training and test dataset[8].

The appropriate choice of k has significant impact on the diagnostic performance of kNN algorithm. A large k reduces the impact of variance caused by random error, but runs the risk of ignoring small but important pattern. The key to choose an appropriate k value is to strike a balance between overfitting and underfitting [9].

3.6 Extra Trees

Extra tree (ET) employs the same principle as random forest and uses a random subset of features to train each base estimator[10]. However, it randomly selects the best feature along with the corresponding value for splitting the node[10].

RF uses bootstrap replicas, that is to say, it subsamples the input data with replacement, whereas ET use the whole original sample. Another difference is the selection of cut points in order to split nodes. RFchooses the optimum split while ET chooses it randomly.

3.7 Naïve Bayes

Naive Bayes is the simplest form of Bayesian network, in which all attributes are independent given the value of the class variable. This is called conditional independence[11].

Advantages [12]

- It requires short computational time for training.
- It improves the classification performance by removing the irrelevant features.
- It has good performance.

Disadvantages [12]

- The Naive Bayes classifier requires a very large number of records to obtain good results.
- Less accurate as compared to other classifiers on some datasets.

IV. CONCLUSION

This paper includes the characteristics of predictive maintenance, and database model made from sensing data, failure history, environment data. And We looked at algorithms for predicting controller failure. Using this basic study, by designing a situation-aware algorithm of the controller, by designing a situation-aware algorithm of the controller, it would be possible to adjust the transmission interval and transmission information according to the status of the controller rather than regular information transmission. In addition, it is expected to further minimize power consumption and improve reliability by judging the change in the controller status information and maximizing the recognition time for the failure situation.

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