BUILDING AN ALGORITHM FOR PREDICTIVE MAINTENANCE

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Predictive maintenance makes it possible to evaluate the operating condition of equipment, helps in identifying failures, or predicts when the next possible error of an equipment is going to happen. Whenever you can diagnose or expect equipment error, you can schedule maintenance in ahead of time, effectively manage inventory, minimize downtime, and enhance the operational potency.

This paper proposes an Algorithm and shows an application of telecommunication equipment's Predictive Maintenance with the help of statistical approaches that could be implemented for an effective maintenance plan, such as Time To Failure and Equipment's Reliability.

Keywords: Predictive maintenance, Statistics, Time to Failure, Reliability.

1. Introduction

Total Productive Maintenance (TPM) is aimed to improve the performance of equipment and its reliability, it is also considered as a key aspect in a quality management system. It strives to increase productivity by investing in appropriate maintenance to reduce losses such as Breakdowns, availability of equipment, minor stoppages that affect equipment efficiency and reduced output quality. Equipment maintenance plays an important role in Total Productive Maintenance, and there are different types of maintenance that are involved such as “Reactive Maintenance”, “Periodic Maintenance”, “Proactive Maintenance” and “Predictive Maintenance”.

In this paper, an Algorithm for Predictive maintenance is proposed, and the statistical methodologies for an effective maintenance plan wer used, such as Time to Failure and Reliability calculations. In predictive maintenance, users and manufacturers, are benefiting from studying the current state of the equipment, the reason that causes failures to equipment and the forecasting the possible time of the next failure. This will help in maintenance planning, since once you can predict a failure, maintenance actions should be done trying to avoid having downtime which will improve the operational efficiency and at the same time helps in organizing

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company’s stock. “Basic understanding of predictive maintenance is continuous monitoring to avoid system breakdown, which will lead to maximize the time interval between consecutive maintenance tasks and reduce the overall production costs”, [1]. “Predictive maintenance is a set of strategies used by the company to lower the impact damage of a component in a telecom site, which has an objective of reducing the operational expenditure and enhance customer satisfaction” [2].

Designing a predictive maintenance plan needs a very well-designed approach for prompt evaluation of the equipment's operating condition and detection of emerging errors. Several factors must be taken into account such as the sources of errors and the number of their occurrence of which we can get it from sensors or even from the key elements of the machine. In addition, the physical dynamics understanding of the system is needed which includes deep understanding of the interactions between different machine signals, the working range of the device and the nature of the readings. Finally, one should clearly think of the main maintenance objective, like error retrieval or maintenance plan evolution. The main purpose of this paper is to design predictive maintenance algorithms that can be used to evaluate the condition of an equipment as well as setting-up an effective maintenance plan withing an appropriate statistical analysis.

This papers is divided into five sections, Section 1: Introduction, Section 2: The Proposed Algorithm Workflow and Algorithm Stages, Section 3: Statistical Analysis used in the Proposed Algorithm, Section 4: Algorithm Application and Simulation and Section 5: Conclusion.

2. The Proposed Algorithm Workflow and Algorithm Stages

A predictive maintenance plan is used to analyze the data provided from the running equipment in order to detect any possible failure that can happen. The idea of having an algorithm for predictive maintenance, is to have an effective plan that lower the cost of maintenance and helps in determining the appropriate time for handling maintenance tasks. A predictive maintenance system uses prediction and tracking algorithms to make the algorithm's end findings available and workable to end users performing the real maintenance duties.

Tracking algorithm is to check the current status of the equipment and define the main factors for having the errors of the equipment. An algorithm for tracking generates information metrics called indices. An index is any system information characteristic whose function changes as the system deteriorates in a predictable manner. Any amount obtained from the information that groups comparable system status together and distinguishes distinct status may be a condition index. Thus, by comparing fresh information against proven indices of defective circumstances, a Tracking algorithm can conduct detection or diagnosis of errors. This information are used to evaluate the equipment present condition and to recognize and help in identifying the errors. “Machine faults are measures of imperfection that physically and systematically change as the machine transitions towards failure” [3].

prediction algorithm is important to detect future possibility of having such error and predict when such error might occur. This algorithm is based on estimating the time of error that might occur, which depends on equipment's present and previous status. Typically, a prediction algorithm forecast the Time-To-Failure (TTF) of the equipment by evaluating the equipment's present status. Prognostic method for machine degradation detection, can both assess machine performance and predict the remaining useful life. Prediction may use modelling, machine learning, or a mixture of both to forecast status indices' future values. These future values will then be used to calculate TTF metrics, which will determine whether and when maintenance should be carried out. The algorithm can then compare the expected values with a limit that defines the equipment's good operation, predicting whether and when the error occurs. A part of the prediction algorithm will be the tracking algorithm, since prediction process will need data from current and past records or sometime simulation is needed when the error is rarely to be happened.

A clear workflow should be stated at first for an algorithm so that its implementation leads to a useful result in forming a predictive maintenance plan.

2.1. The Proposed Algorithm Workflow: A workflow to build a predictive maintenance algorithm is shown in Figure 1.

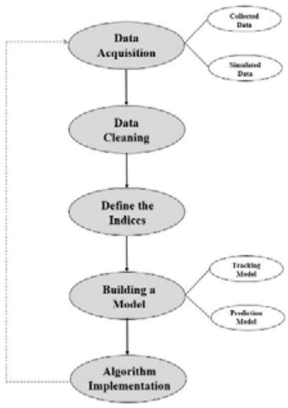

Fig. 1. The Proposed Algorithm Workflow

In any algorithm, you will have to follow different stages which is considered to be basics for running the algorithm. Hence, when you plan to create a detection model (for tracking) or a forecast model (for prediction) starting with data that defines your scheme in a range of good and defective circumstances will be one of the major steps. Evolving such a model involves the identification of suitable status indices and the preparation of a model for their interpretation. This method is likely to be incremental as you attempt distinct indices and distinct designs until you discover your application's best model. Lastly, the algorithm is deployed and integrated into your equipment tracking and maintenance systems.

The Workflow preparation stage consist of five major points: The Data Acquisition, The Data Cleaning, Defining the Indices, Building Models and Algorithm Implementation.

2.2. Data Acquisition*:* “Data are the facts that are collected, analyzed and summarized for presentation and interpretation. All the data collected in particular study are referred to as the data set” [4]. Data is a set of information that is collected from the experimental units of which could be identified as Humans, Machines, Animal or anything under study. The first step in evolving predictive maintenance algorithm is data collection. "The data acquisition process transforms the sensor signals into domains that have the most information to represent the condition of the equipment or a fusion of several domains" [5]. For a good plan of predictive maintenance, data collection plays an important role of which the process of the data collection might require a large data base in some circumstances when tracking a time series data.

Data can be collected in three different status, Status 1: When the system is normally working, Status 2: When the system is working with error conditions and Status 3: When the system in not working. When regular maintenance for the equipment is performed, then it will be very difficult to have errors and so we will have limited data for failure datasets. For that reason, one could think of simulated data. The more data you can collect, the more accurate (power) you will get and the lower the level of significance will be.

2.3. Data Cleaning*:* "Data preparation is an indispensable step in order to convert various data forms and types into proper format that is meaningful to machine learning predictive model" [6]. After the data acquisition stage, an important step in this algorithm is to transform your data into a form that makes it easier for defining the indices. This will include cleaning data from outliers or even from missing values of which this part is considered to be the simple technique. Data cleaning is usually done by applying the “Data Explore” to summarize the values of the data and then look for extreme values, which are usually defined as values outside the expected range, then we investigate whether these values are considered as outliers or not. As for the missing values, different methods can be used, like we can replace the missing value by the computed average, in other cases, it could be replaced by similar cases or even delete such cases, all depends on the critical case of study and the historical data available for such cases.

Once you have a good knowledge about your equipment and the type of data you have, the data cleaning technique will be easier to be selected. Statistical software such as SPSS can be used for the data cleaning issues by looking for extreme values, replacing missing values or even reverse recoding when needed.

2.4. Define the Indices*:* Any characteristic that can be helpful to distinguish between normal and improper operations or to predict Time to Failure can be an index. The identification of indices in your system information, whose conduct changes with the equipment degrading in a predictable manner, is one important step in the growth of predictive maintenance algorithms. "Organizations face both new opportunities and challenges, one of them is predictive analysis using computer tools capable of detecting patterns in the analyzed data from the same rules that can be used to formulate predictions" [7]. Examples of indices are some values resulting from 'Simple analysis' by finding some numerical measures such as the average over time, 'Complex analysis' that explains or describes the changes in field over time, 'Model-Based analysis' when sometime looking for estimating parameters.

The most appropriate indices to be stated are related to your system understanding as well as the sort of scheme that you have.

2.5. Building a Model: The tracking or prediction model is the core of the predictive maintenance algorithm. This model examines derived indices to determine the system's present condition (error tracking and identification) or its prospective condition (Time to Failure forecast).

2.5.1. Error tracking and identification: The tracking and identification of errors depends on the use of one or more conditions to determine whether the function is safe or bad and between distinct kinds of errors. A straightforward fault-tracking model is a limit value for the measure of a fault when it is surpassed. In order to determine the probability of a specific failure situation, another model could compare a condition index to a statistical distribution of measurement values.

One of the tracking measure that can be calculated is the Mean Time to Repair (MTTR) measured by getting the total period needed for all repairs during the year and then divided by the number of repairs made during the same period. This measure will be also used in the predictive maintenance plan, since this period should be taken into consideration when assigning a date for maintenance.

$$MTTR = \frac{Total\ Maintenance\ Time}{Total\ Number\ of\ Repairs} \tag{1}$$

2.5.2. Time to Failure Prediction: To predict the time to failure, a model should be generated and as examples on such models we can see the following:

- A model that corresponds to a condition index's time progress and foresees how long it will take before the condition index reaches certain limit values to indicate an error.

- A model which matches up the time progress of a condition index from failing systems to calculated or computer generated time series. Such a model can calculate the present system's most probable time to fail.

The Mean Time between Failure (MTBF) is an estimate of the reliability of the equipment. It is calculated by using the total operated time divided by the total number of failures. In addition, one can calculate the failure rate of the equipment, which is 1 divided by the MTBF to get an idea about the failure rate per year of this equipment. Such measures are used for prediction model.

$$MTBF = \frac{Total\ Operation\ Time}{Number\ of\ Failures}, \tag{2}$$

In many cases, the Time to Failure might be predicted by using dynamic system models, using many techniques such as threshold and survival analysis of which the Weibull Distribution is mainly used.

“From a maintenance process perspective, Remaining Useful Lifetime estimation is very useful for long-term planning of spare parts supply and maintenance scheduling. On the other hand, failure prediction is more useful for handling unexpected failures that might happen in a short time-span” [9].

2.6. Algorithm Implementation: Once you are done with your data by processing it properly and then by generating an appropriate prediction model, you use your algorithm and incorporate it into your system. In addition, according to your systems’ technical and other details, you decide whether to implement your algorithm on the cloud, storage arrays or a mix between them by using the storage arrays for pre-processing and when setting the algorithm properties, whereas use the cloud for running the predictive model.

3. Statistical Analysis used in the Proposed Algorithm

In the main heart of the proposed algorithm there are different probability distribution could be used in order to prepare studying the equipment reliability and plan for predictive maintenance. In this section, the most commonly used probability distributions are summarized, followed by the technique used to determine the best fit distribution and then summarizing the way how to calculate the equipment reliability. Such Analysis are used to determine the key indices of the equipment and getting an idea about the efficiency level of the equipment before building a tracking model of even predicting the time to failure or what is also called as Remaining Useful Lifetime.

3.1. Commonly used Probability Distribution: There are many probability distributions that are used in industrial engineering, we are going to list in this report the most commonly used probability distribution in the domain of telecommunication sector.

3.1.1. Exponential Distribution: “The exponential distribution is one of the most commonly used distributions in reliability and is generally used to predict the probability of survival to time t” [10]. Although the exponential distribution is commonly used to model component repair, it is not well suited for this task. It is relatively accurate representation of electronic component time to failure and should only be used for reliability prediction during the constant failure rate or random failure phase of operation. The exponential Distribution has the parameter $\mu = Mean$ and CDF (Cumulative Distribution Function):

$$F(t) = 1 - e^{-\frac{1}{\mu}t} \; for \; t \geq 0 \tag{3}$$

Noting that the sum of individual exponential random variables is an exponentially random variable.

3.1.2. Normal and Lognormal Distribution: “The normal (Gaussian) and lognormal distributions are continuous statistical distributions that can be used to model a large number of varying types of system repair behavior” [11]. In telecommunications systems, the failure can many times be well represented by the exponential distribution, whereas, Repair is more often well modeled by normal or lognormal random variables. The lognormal distribution is simply the distribution of a random variable whose logarithm is normally distributed. It would be very unusual to use a normally distributed random variable to model the time to failure of a component in a telecommunications system. Exceptions to this might occur in submarine cable systems or wireless propagation models.
The Normal Distribution has the following parameters: μ (the mean) and σ (the standard deviation); The C.D.F is given by:

$$F(t) = P\left(T \leq \frac{t-\mu}{\sigma}\right) = \varphi\left(\frac{t-\mu}{\sigma}\right) \tag{4}$$

3.1.3. Weibull distribution: "Generally, all but the most sophisticated telecommunications systems failure performance models use exponentially distributed time to failure owing to the memory less property" [11]. The parameters of the distribution provide a great deal of flexibility to model systems in which the number of failures increases with time (bearing wear), decreases with time (some semiconductors), or remain constant with time (failures caused by external shocks to the system). The Weibull Distribution has the following parameters: $\delta = scale\,parameter$ and $\beta = Shape\,parameter$ With CDF (Cumulative Distribution Function) [12]:

$$\boldsymbol{F(t)} = 1 - e^{-\left(\frac{t}{\delta}\right)^{\beta}} \; for \; t \geq 0 \tag{5}$$

3.2. Technique used to determine the Best Fit Probability Distribution: Data might follow different probability distributions; By using Statistical software such as SPSS or MINITAB, the "Individual Distribution Identification" is able to determine the best-fit distribution of the given data.

After running the “Individual Distribution Identification”, at first, one should look for the significant p-value ($P_v > 0.05$) to check whether this distribution fits the data, then for significant distribution we use the Anderson-Darling parameter to check the Best Fit Distribution. The Lowest the Anderson-Darling, the best the distribution will be.

As an example, Figure 2 shows the result of the best fit distribution when studying the distribution of ‘Time to Repair a submarine Fiber optic Cable’

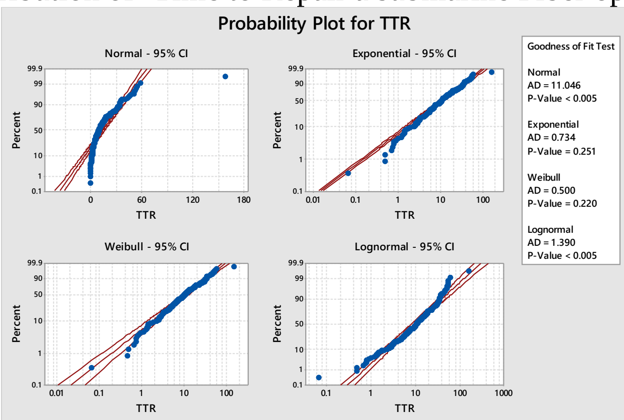

Fig. 2. Studying the best fit distribution for Time to Repair Data set

Result shows that the given data fits the Exponential and Weibull Distribution (since both $P_v > 5\%$), so no evidence to reject the hypothesis of fitting the distribution. Hence, it is better fit of Weibull distribution as it has the lowest Anderson-Darling statistic (AD) value (AD=0.500).

3.3. Equipment’s Reliability: Analyzing equipments' reliability helps organizations in general to improve and provide high quality service for their customers. This will also help to gain an excellent relationship with their customers.. Reliability is attained after achieving the desired outcomes required from a designed system. Indeed, reliability is best defined as “the duration or probability of failure-free performance under stated conditions” [11]. However, the probability that an item will perform its intended function for a specified interval understated environmental conditions also reflects a complementary definition for the core meaning of reliability. In advance, the reliability function is a mathematical expression, which analytically relates the probability of success to time, and is defined by the following expression [13]:

$$R(t) = 1 - F(t) \;\; for \; t > 0 \qquad (6)$$

Of which $F(t)$ is the cumulative probability function (CDF) of the Time to Failure (TTF).

4. Algorithm Application and Simulation

As an Application of this predictive maintenance algorithm, we will talk about the Remote Radio Unit (RRU) in the telecommunication sector.

An RRU is defined as “A wireless base station (also known as a cell site or wireless base transceiver station, BTS) is a piece of equipment that facilitates wireless communication between user equipment (UE) and a network” [14]. This RRU can handle calls for a certain range that needs to be defined by the manufacturer and experts as well. When the number of calls exceeds this range it goes for warning level before the Threshold value, that is, before the Error occurs which causes Drop Call.

The main purpose of our Algorithm is to check and predict the failure time of this RRU equipment in order to plan for maintenance accordingly. The Input and Output result of the proposed algorithm should contains at least the following Information:

4.1. Input Information:

1. Data Set: Historical data is needed which include the equipment’s overload value that is monitored along with the equipment status of the equipment.
2. Equipment’s overload threshold value as well as a Warning level of such overload, which is usually defined by the domain expert or the manufacturer.

4.2. Output Information:

1. A graph that shows the performance of the equipment in the historical data, showing the threshold level at the same time and some warnings the equipment might has when reaching a certain level of overload.
2. A warning message from the observed values will pop-up when reaching a certain level of indicator.
3. A Message for detailed information about the equipment that helps the user to determine the current status of the equipment along with the estimated date of the next error so that a predictive maintenance is applied.

A random data set has been generated for this example and presented in table 1, which include the historical data of day by day equipment’s overload records for 1 year along with the equipment, and check the equipment’s overload value based on the defined regular load of the equipment that is defined by experts.

Input Information:

1. Data: Day by Day Equipment's Status and Overload Value (Table 1).

Table 1: **Day by Day Equipment's Overload Value & Equipment Status**

Day #	Equipment's Overload Value (in thousands)	Equipment Status
1	7	Working
…	…	…
32	16	Warning
…	…	…
330	28	Error
…	…	…
365	4	Working

2. Equipment's Overload Warning value = 15 (defined by an expert)
3. Equipment's Overload Threshold value = 25 (defined by an expert)

Output Information:

1. Graph output (Figure 3): This graph summarize the current status and shows the history of the equipment's overload values, it highlights the bars as Red for Errors, Green for the warnings and Blue for the normal status.

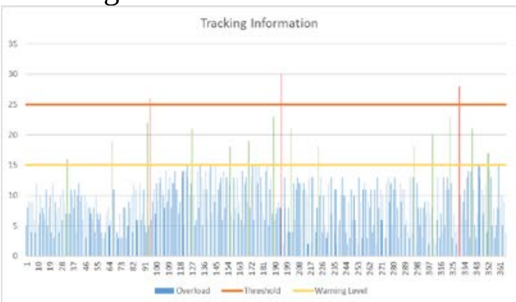

Fig. 3. Equipment's Tracking Information for Equipment's daily Overload

In this figure, we can see that there are 3 failure status in the monitored year and there are more than overload value that falls within the warning range.

2. Warning Message (Table 2): this message will pop-up once an equipment's Overload value exceeds 15 but still below the threshold value and gives you the following summary:

Table 2: **Warning Message**

Warning Date	18-Dec-18
Equipment's Overload Value	17
Last Warning Date	6-Dec-18
Number of Warnings since Last Error	2

3. Detailed Information Message (Table 3): This will include the equipment current reliability, the estimated time to failure which is computed based on the appropriate probability distribution of the Equipment's Overload variable.

Table 3: **Detailed Information Message**

MTBF	110.67 days
Date of Requested Information	31-Dec-2018
Estimated Date for the Next Error	16-Mar-19
Number of Days Left before the Expected Error	75 days
Equipment Reliability	86.9%

The Pop-up Message with such information, are calculated based on the input data, which applies the appropriate calculation using the best fit probability distribution of the data. This Pop-up message will give some details about the Mean Time Between Failure (MTBF) based on the historical data of errors occurred, as well as the expected date for the next error along with the equipment reliability which is the % that the equipment will be reliable before the next expected error.

5. Conclusions

Evaluating the current condition of an equipment, as well as predicting the possible time of having a failure in the future, are the main targets of companies in order to improve their efficiency and decrease the downtime possibilities they might face. Predictive maintenance if applied properly would help reaching such goals with the application of well-designed algorithm for that issue.

This paper suggested workflow for the algorithm evolution with an explaination of each suggested stage, the Data Acquisition, Data Cleaning, Forming the Indices, Building Models and Algorithm Implementation. The use of statistics is very important when building the tracking and prediction algorithm. For this reason, a brief of the most commonly used probability distribution in this domain has been summarized along with their cumulative probability function which is used in the calculation of equipment's reliability.

Finally, an algorithm application and simulation has been stated to summarize the input and output information of the algorithm, the warning and detailed message that can be generated about the equipment which includes information about the mean time between failures, as well as the next expected error along with the equipment reliability. This will help the use to build an effective plan for the maintenance of which we call it the predictive maintenance plan.

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