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Optimization of uses, Production and Overall cost of a plant through Dynamic Prescriptive maintenance

Bobby D. Chilami, Ratan V. Karate, Omkar S. Kakate, Somnath R. Shintre, Shivam M. Shinde.
Project Guide: prof. Mr. M. S. Bhandigare .
[1]*Sant Gajanan Maharaj College of Engineering Mahagaon, Gadhinglaj- 416501, Maharashtra, India.*

Abstract: *Dynamic Prescriptive Maintenance covers new trends and techniques in the field of predictive maintenance, which has been superseding traditional management policies. It also presents suggestions for how to implement a predictive maintenance program in a factory/premise or a large-scale industry. Predictive maintenance primarily involves foreseeing breakdown of the system to be maintained by detecting early signs of failure in order to make maintenance work more proactive. In addition to the aim of acting before failure, it also aims to attend to any fault, even if there is no immediate danger of failure, to ensure smooth operation and reduce energy consumption. This practice has been adopted by various sectors in manufacturing and service industries in order to improve reliability, safety, availability, efficiency and quality as well as to protect the environment. This project is aimed on creating a website, where any industry/entity can seek for the implementation of predictive maintenance program. And to provide precise and unerring results. The implementation involves practice of automation for prediction of future maintenance points using live data and the provided old data.*

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I. INTRODUCTION

Maintenance is an important factor in quality assurance and in some cases determines the long-term success of a company. Poorly maintained resources can cause instability and partially or completely pause the production. Malfunctioning machines or complete breakdowns can become a costly process for most companies.

The purpose of maintenance is to ensure the maximum efficiency and availability of production equipment, utilities and related facilities at optimal cost and under satisfactory conditions of quality, safety and protection for theenvironment.

Maintenance, as a profession and as a corporate practice, has evolved a lot in the last 50 years. As a profession, maintenance isn't just the domain of trades-people. It also includes engineers and planners to manage maintenance practice. In world-class companies, maintenance is now seen as an integral part of business operations because it can have a significant impact on corporate profitability.

Over the last 50 years, the techniques for performing maintenance have also significantly changed. While maintenance used to be reactive to breakdown, maintenance in world-class companies is now an activity that is much moreproactive.

With the increasing integration of systems, maintenance strategies are placing more emphasis on techno-economic than technological considerations. Existing maintenance strategies include time-based maintenance, where maintenance actions are performed at failure (corrective maintenance) or based on system age (age-based maintenance), and condition-based maintenance, where maintenance decisions are provided based on the health condition of the system. Prescriptive maintenance has gained popularity in recent years

It extends the concept of failure prediction by predicting maintenance measures and prescribing a course of actions based on the historical and incoming real-time data. Prescriptive maintenance strategies are updated based on the observed/predicted degradation parameters and system state, whereas in conventional time-based maintenance, decisions only rely on historical data without considering updates.

In this project we are going to implement the prescriptive maintenance which uses advanced analytics to make predictions about maintenance. These prescriptive systems can make recommendations for user about the maintenance so user can act on those recommendations.

The old method: time-based maintenance

Maintenance has been conducted for many companies for decades in the same way– it's based on manufacturers' recommendations. So basically in this method manufacturers give predefined recommendations that how to maintain machine based on engineers or R&D teams insights which created the product. The drawback of these maintains is it takemore time and the It required more manpower.

The most widely accepted current method: condition- based maintenance:
With the help of advance scale computing technology, like embedded sensors in valuable equipment, companies can make use of condition-based maintenance. Instead of maintaining equipment based on a pre-defined schedule, this type of maintenance is very effective to determine the need for maintenance for actual condition.

The advanced method: predictive maintenance:
Predictive maintenance goes step further from Condition-based maintenance. Once row data is coming from equipment in real-time from companies. Advanced analytics are used to identify feature asset reliability risks that could impact on machine.

The future: prescriptive maintenance:
Prescriptive maintenance is the future. To make predictions about maintenance It uses advanced analytics, but the main difference is that prescriptive systems not only make recommendations but also act on recommendations.

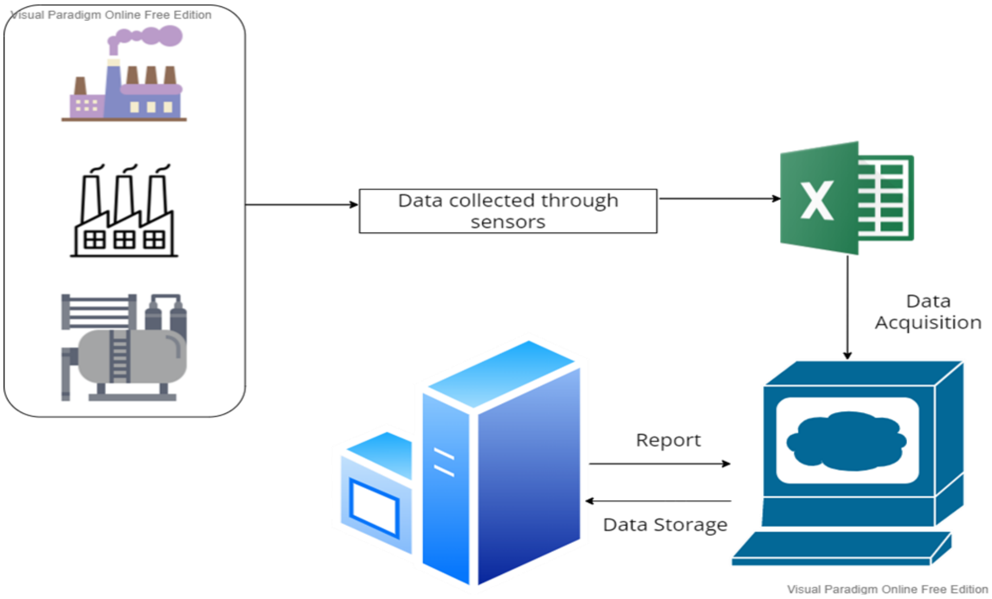

Fig 1: System architecture

PROPOSED SYSTEM
System Architecture

Our proposed system uses the concepts of lossless textcompression mentioned in this paper.

System Architecture is shown in Figure

1Decomposition Model
Abraham Maslow writes, "I suppose it is tempting, if the only tool you have is a hammer, to treat everything as if it were a nail". This is the situation that aspiring data scientists find themselves in when analysing time series data. The seasonal decompose function from Python's Stats models library is the hammer, and every time series data is just another nail. Decomposing our time series is an important step in improving forecast accuracy and creating causal insights.

Why should we decompose our time series data?
Time series decomposition refers to the method by which we reduce our time series data into its following four components:

- Trend [*T*]
- Cycle [*C*]

- Seasonality [*S*]
- Remainder [*R*]

The combination of the components in time series canbe of two types:

- Additive
- Multiplicative1)Additive time series

if the components of the time series are added together to make the time series. Then the time series is called the additive time series. By visualization, we can say the time series is additive if the increasing or decreasing pattern of the time series is similar throughout the series. The mathematical function of any additive time series can be represented by:

y(t) = level + Trend + seasonality + noise2)Multiplicative time series

If the components of the time series are multiplicative together, then the time series is called the multiplicative time series. By visualization, if the time series is having exponential growth or decrement with time then the time series can be considered as the multiplicative time series. The mathematical function of the Multiplicative time series can be represented as.

y(t) = Level * Trend * seasonality * Noise

The image below represents the additive and multiplicative time series.

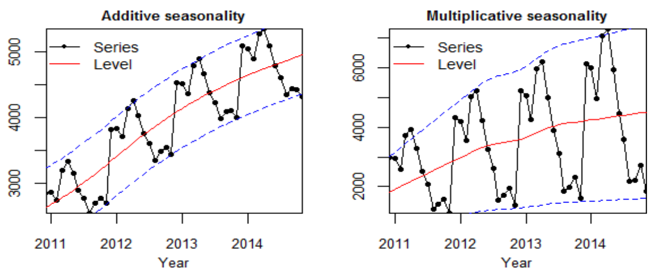

Fig 2. Additive time series, Multiplicative time series

In the above image, we can see the difference in the growth of values. In additive, it is quite slower and has a proper trend but on the other hand, we can see that the time series is growing exponentially with the time

Problem Number 1: Predicting TD1 TD2 PD1What Is TD1 TD2 And PD1?
TD1: So basically, TD1 means the temperature of a machine. It gives the temperature data of any part of a machine like a large machine has two rotors then the TD1 willbe the temperature of first rotor.
TD2: TD2 is also the temperature of a machine but it gives a data of another part of the machine. Like as if the machine has two rotor and TD1 is the temperature of first rotor then the TD2 will be the temperature of second rotor.
PD1: To decrease the temperature of TD1 we have to apply some amount of pressure i.e., known as PD1.

Nature of Data	
Minimum Value	16.21661
Maximum Value	216.60458
Average	113.740393
Median	171.30838
Mod	20.9276

based on these three factors we are going to predict the maintenance of system. These three factors can be directly and inversely proportional to each other according to themachine architecture.
So, in this project till now we first predict the further values of each factor TD1, TD2 and PD1 separately using following steps and at the last we plot a graph for each factor.

There are various steps involve in this process these are as follows.
Step 1: Cleaning the Data.
Determining Nature of Data: The provided data could have faulty values, unknown characters, irrationally large or small values, etc. The first step in cleaning the data is knowing the data; thus, we calculate the Minimum value, Maximum value, Average, Median and Mode of the data.

The above data in the table gives characteristics of a certain data provided. These factors are calculated to determine the nature of the data.
Setting a Range: The next step is to set a range for the right data. the range is the spread of data from the lowest to the highest value in the distribution. It is a commonly used measure of variability.
Along with measures of central tendency, measures of variability give descriptive statistics for summarizing the data set. The range is calculated by subtracting the lowest value from the highest value. Sometimes the range is hard to calculate as the data gets spread equally from low end to high; in such cases, Interquartile range is taken into consideration. While a large range means high variability, a small range means low variability in a distribution.
The range can vary between any natural numbers, setting up a range is important when cleaning the data. This process ignores all the notorious readings which could throw- off the prediction results by a large margin.
Anomaly Detection: It is a method which find the anomaly's (the identification of events that do not conform to the expected pattern). It will be different from the pattern. For example – detecting stones or unwanted material in rice, detecting part failures from machine. Below is the plotted graph of a certain machine whose Air Temperature attribute isprovided as data; this also shows a deep spike which is identified as an anomaly.

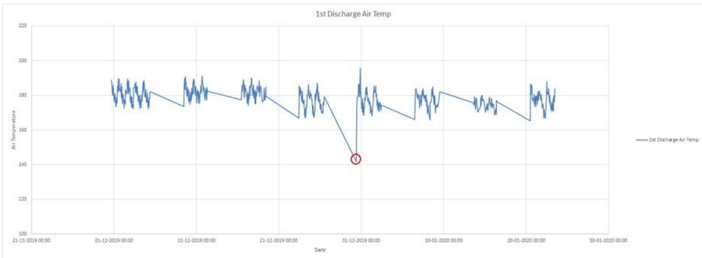

Fig 3. Anomaly Detection

Filling missing values: The data which is provided may miss some values after the above steps, these missing values should be filled for successful prediction. Thus, techniques like Moving average, Autoregression are used to fill the gaps between data.
Step 2: Applying Auto regression.
Before applying Auto regression, we first have to calculate the following properties based on the provided or the observed data.
Let's assume some data of an Air Pump pressure over time in days shown in below figure.

Fig 4. Filling missing values

The first thing to do after cleaning the data is to identify the above-mentioned properties through seasonal decomposition.The following code in Python is used to achieve seasonal decomposition.

Trend: For prediction of next or future variables, trend is calculated based on the data provided from the system. It shows the data flow and helps to understand the observed data.

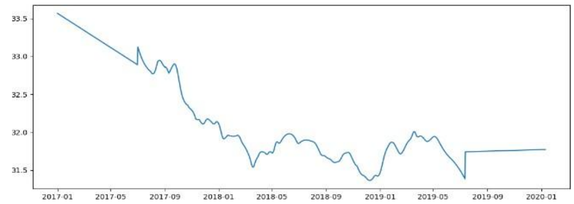

Fig 5. Trend

The above figure shows the trend of the observed Air Pump Pressure data over time. This gives a clear understanding that the trend here is downward and thus the future points will be too. The figure is a graph of the trend values over time.

Seasonal: The next part is to identify the seasonal component. This in the above example can be seen over a period of year and plotted graph should look like:

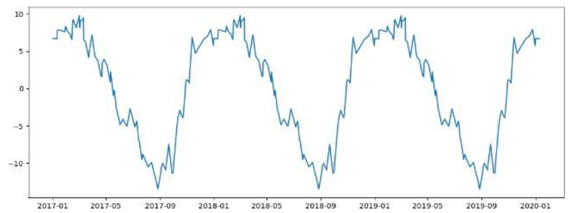

Fig 6. Seasonal

Residuals: The residuals or resid depicts the difference between observed and fitted values. Residuals are important for the evaluation of goodness of a fitted model.

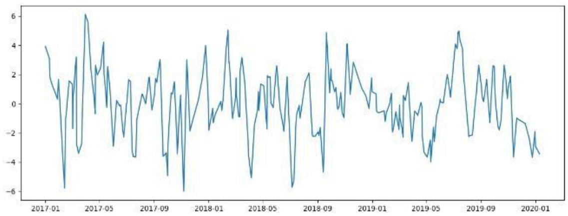

Fig 7. ResidualsPredicting the future values:

Auto regression: Auto_regression is a time series model that uses output from previous time steps as input to a regression for predicting values of next time step. It is a very simple idea that can result in accurate forecasts on a range of time series problems.
The python library statsmodels gives all the functions required in prediction of the future values. The function AutoReg is used to run auto regression on the observed data.

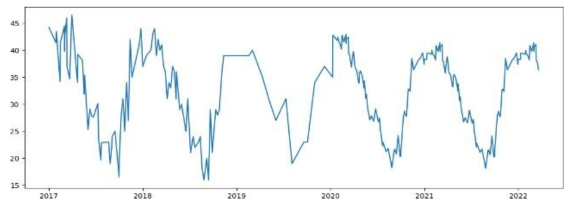

Fig 8. Auto regression

The above figure shows the observed and then the predicted values plotted on a graph over time. This graph is generated by the below python code.

II. CONCLUSION

Machines were maintained when they started to break, or maintained on an equal interval basis, but using Prescriptive maintenance and optimal RBD paths we developed a project which will change the maintenance

and planning of a whole plant. It is aimed to optimize all the safety and risk factors, optimize the running time and maintain the cost.
The risk of breaking will be reduced and life expectancy of the machines will be increased seemingly.

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