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Internet of Things – A Predictive Maintenance Tool for General Machinery, Petrochemicals and Water Treatment

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Abstract

Improper and unnecessary maintenance actions can result in a waste of resources, time, and money. Training and education play an important role in the successful implementation of a maintenance strategy. The Center for Predictive Maintenance (CPM) at the University of South Carolina has developed a demonstration methodology and tool that can be used to educate and train users extending from maintainers to leadership on the maintenance process from fault to maintenance action. This overall methodology has been developed so that it can be applied to a variety of industries including general machinery, petroleum and petro chemicals, and water treatment. All of these industries have a need for successful implementation of predictive maintenance programs and this demonstration methodology can be used to train and educate users. This demonstration tool will walk an audience through the maintenance process starting with the collection of sensor and historical data. Then it will show the analysis of the data through modeling and statistical analysis techniques. Finally, the data and results are displayed in unique dashboards that provide personnel with the information needed to make educated decisions on the condition and maintenance of their system.

Keywords: Predictive maintenance, Internet of Things;

1. Introduction

Traditionally, the two most common strategies for maintenance management were either reactive or preventive. Reactive maintenance is a failure-based strategy where maintenance actions are performed only after the component has failed. Preventive maintenance is a time-based or usage-based strategy where maintenance actions are performed after a set amount of time. Both types of strategies have their strengths and weaknesses. Reactive maintenance can save money in the short-term, but long-term can lead to higher

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repair costs and longer down-times. Preventive maintenance results in higher reliability but can be more costly if maintenance is performed before it is actually needed.

In order to achieve both high reliability and low cost, a predictive maintenance strategy would need to be implemented. Predictive maintenance is condition-based and maintenance is performed only when the component requires it. Predictive maintenance also allows for predictions to be made on when a component will fail which allows maintainers to be prepared for that failure before it happens. Implementing predictive maintenance can provide a company with an optimal maintenance strategy at a low cost with the highest reliability.

2. Background

Maintenance is a large part of any industry and depending on the industry can represent between 15 and 60 percent of total costs. In the United States, industries spend more than $200 billion each year on maintenance. Recent surveys have shown that there is a need for better maintenance implementation. Improper and unnecessary maintenance actions make up almost 33% of maintenance costs [Mobley, 2002].

A successful implementation of predictive maintenance can result in many benefits including reduced maintenance costs, increased readiness and availability, and increased feelings of safety. In order to achieve these benefits, predictive maintenance requires new processes and technologies. This is where training and education become important in the success of a predictive maintenance strategy. If maintainers and other users are not properly trained on the different processes of predictive maintenance then the results of cost-savings and high reliability will not be seen.

The Center for Predictive Maintenance has developed an Internet of Things (IoT) based methodology for creating a demonstration that can be used to train and educate users on predictive maintenance. This methodology can be applied to various industries such as general machinery, petroleum and petro chemicals, and water treatment. Even though these industries involve differing maintenance needs and procedures, the same IoT methodology for predictive maintenance can be applied.

3. Internet of Things

The Internet of Things (IoT) refers to a network of interconnected objects or things [Atzori et al, 2010]. These objects are able to communicate and interact with each other regardless of physical location. In the maintenance world, these objects are embedded with sensors that monitor the condition of the object. Over the years, the IoT has increased in popularity in maintenance. It provides a framework for users to connect and collect data from all the components and systems that they are monitoring. This data is collected and analyzed in real time to identify and extract meaningful relationships in the data. The collected data can also be compared to previous trends that were calculated with historical data. In the IoT framework, not only are the physical components and systems connected, but also every user in the maintenance process is connected. This means that a user does not need to be physically with the asset to know its condition. The information a user would need is presented to them with real-time dashboards and alerts.

The IoT has changed the way users think about data. If an IoT framework is being implemented, then there is a large amount of data is continuously being collected in real-time from the network of sensors. This data being collected from the components and systems is full of valuable insights and useful relationships but it also presents some difficulties. One problem is how to manage and extract value from the IoT data. Previously, data could be stored locally but this approach has its limits on storage and efficiency. In order to quickly store, manage, and analyze IoT data, cloud computing will need to be used.

Cloud computing uses a network of servers hosted on the internet to store, manage, and analyze data as opposed to doing it locally on one machine. This setup allows resources such as computing power and storage to be shared across the network of servers providing a large capacity for storage and processing power. The cloud framework can be divided into different areas that include cloud storage, cloud applications, and cloud infrastructure as shown in Figure 1. The cloud storage contains databases for the collected and processed data. Cloud applications include programs that a user might need access to. This includes programs for analyzing the data, creating diagnostic and prognostic models, generating reports and work-orders, and real-time dashboards containing information. The cloud infrastructure refers to the setup of the network. Having the data and programs stored in the cloud allows a user with the proper credentials access no matter where they are located. There is also the benefit that they can view the results and data from any device because the programs are not located locally on their machine but instead in the cloud.

Cloud computing addresses the problem of storing and managing the IoT data but it doesn't solve the problem of how to analyze the data. This is where the research area of big data analytic fits in. Big data is a term used to describe large amounts of data sets that can be analyzed for extracting patterns, trends, and relationships. There are large amounts of data associated and generated from maintenance. Data directly related to the condition of a component or system can be historical or current (real-time). Historical data includes logistical data from maintenance records which can also include a user's experience and knowledge. Historical data also includes previously collected sensor data. Current data includes the data being collected from the sensors. Other types of data that might impact the condition of a component or system can also be collected such as the weather or environmental variables. Data and knowledge from technical manuals and reports also have value. In order to extract useful information from all this data, advanced analytic techniques for big data will need to be used.

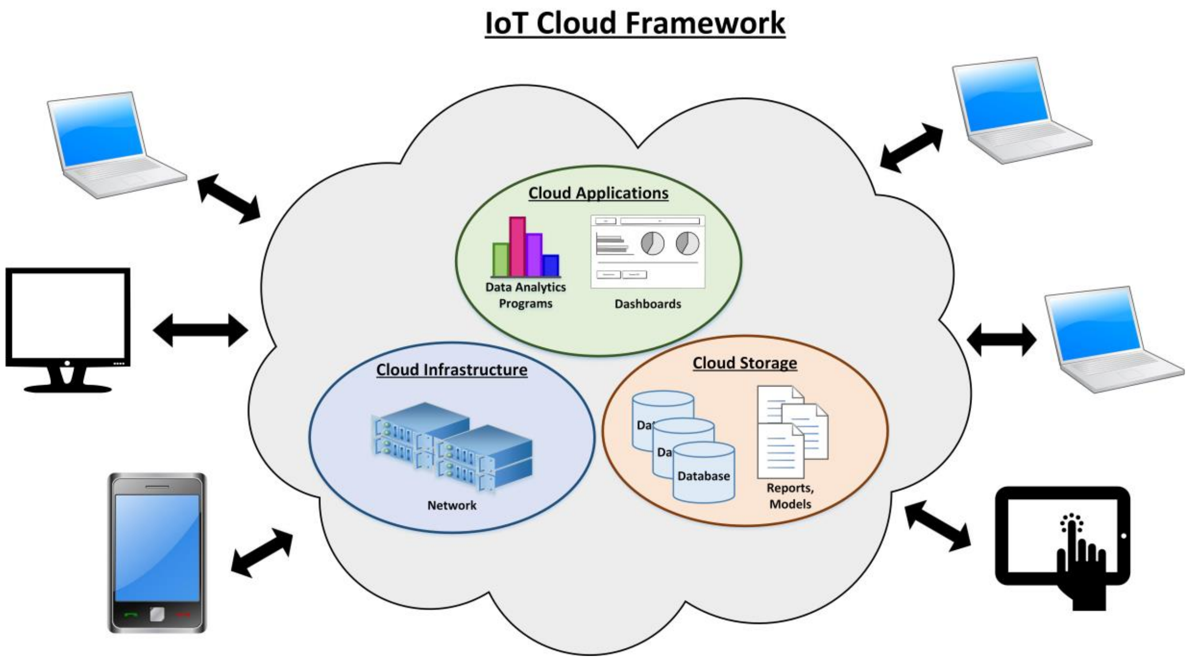

Figure 1: Internet of Things cloud framework.

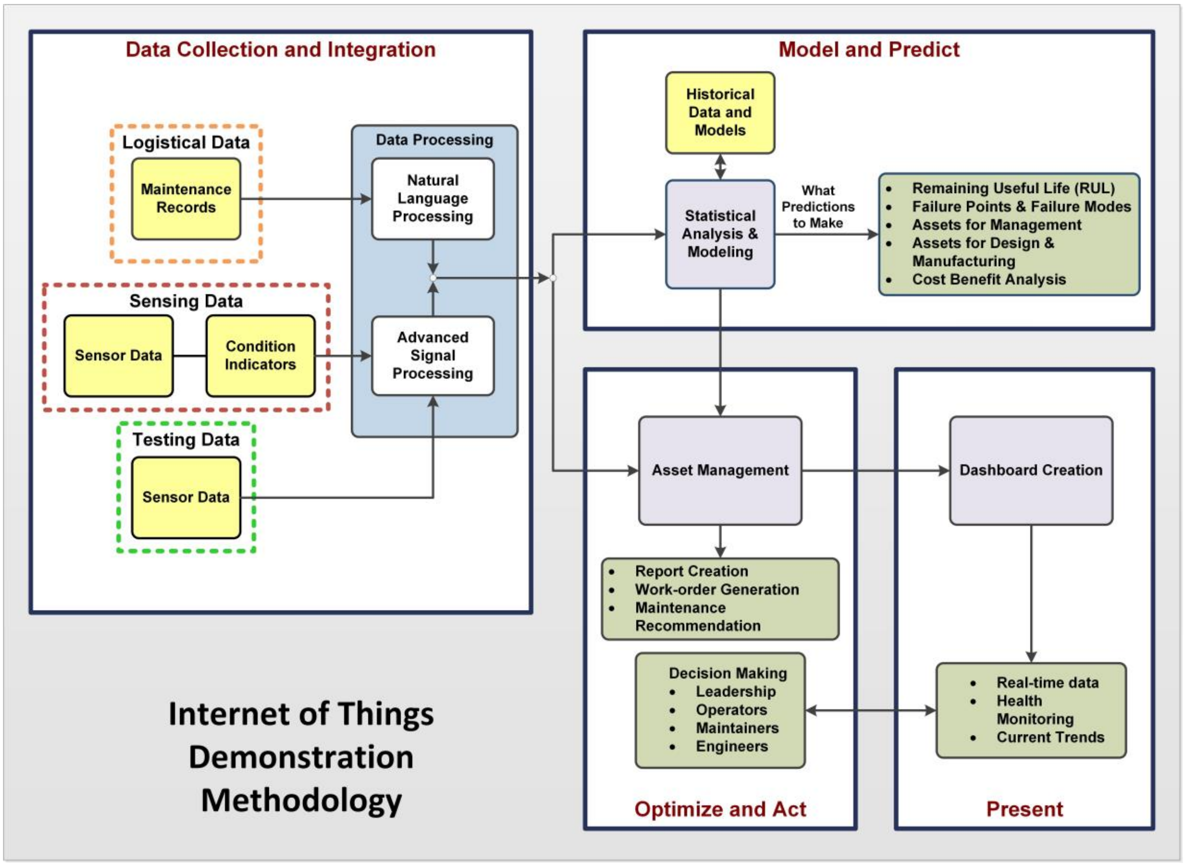

Figure 2: Internet of Things demonstration methodology

4. Methodology

Predictive maintenance is a system's level approach that can be broken down into four areas: data collection and integration, model and predict, optimize and act, and present. The developed methodology creates a demonstration that addresses those four areas. Figure 2 shows the demonstration methodology. The goal of the demonstration is to allow a user to see the whole process from start to finish.

4.1 Data Collection and Integration

Data collection is a very important step in predictive maintenance and data can come in three different types: logistical, sensing, and testing. Logistical data contains information on the maintenance actions performed on a component or system. Sensing data is collected from sensors on the component or system. The last type of data is testing data, this is collected sensor data from a test stand that can be used to validate and refine models and relationships found in the logistical and sensing data. After collection, the data will need to be processed before it can be stored or analysed. Written text from logistical data can often contain mistakes and gaps due to human error. Techniques such as natural language processing will need to be done in order to transform the text into a useable form [Bokinsky et al., 2013]. The collected sensor data will be processed using techniques such as advanced signal processing. Advanced signal processing helps in the extraction of relationships between sensors [Coats et al., 2011].

Data integration will then be done to combine the different types of data into one set. Combined, the data can give a more complete picture than one set could on their own.

4.2 Model and Predict

After the data has been collected and processed, it can be analysed through models and predictions. Data can be used to address many different questions depending on what the user's goals are and what predictions they want to make. For example, if the user is interested in information about the life of the component or system they are monitoring then diagnostic and prognostic models can be created to show information such as remaining useful life. In order to create diagnostic and prognostic models, historical data would be used to create an initial model for detecting failures. The current real-time data would compared against those models to see if a failure exists. The current data is also stored and later used to refine the initial fault models. Other predictions can include models for cost-benefit analysis, failure points and failure modes, and design and manufacturing.

4.3 Optimize and Act

The next step involves asset management. After the data has been used to create models and predictions, the results of these models will need to be interpreted. This step results in the creation of reports, generation of work-orders, and recommendation of maintenance actions. The types of users that would be using these results for decision-making include leadership, operators, maintainers, and engineers.

4.4 Present

The final step is to present the data and results in the form of a dashboard. These dashboards are created to be tailored to fit the needs of the user so that they only view the information important to them. These dashboards allow a user to view data in real-time, look at current trends, and monitor the health of a system.

5. Applications to Industry

The IoT methodology can be used to develop predictive maintenance tools for the advancement of predictive maintenance in industries such as general machinery, petroleum and petro chemicals, and water treatment. Even though these industries involve differing maintenance needs, the same IoT methodology for predictive maintenance can be applied to all of them. It is important to advance the maintenance practices of these industries because they play a vital role in our lives. In the area of general machinery, components have usually been repaired on a time-based schedule which leads to unnecessary maintenance repairs and increase in maintenance costs. The petro chemicals industry is facing large growth and with that a need for efficient maintenance practices. One important area of the water resource industry is the desalinization of water. In order to keep the cost of desalinization down, unscheduled maintenance needs to decrease. Predictive maintenance can address all of these problems and lead to a reduction in unscheduled and unnecessary maintenance.

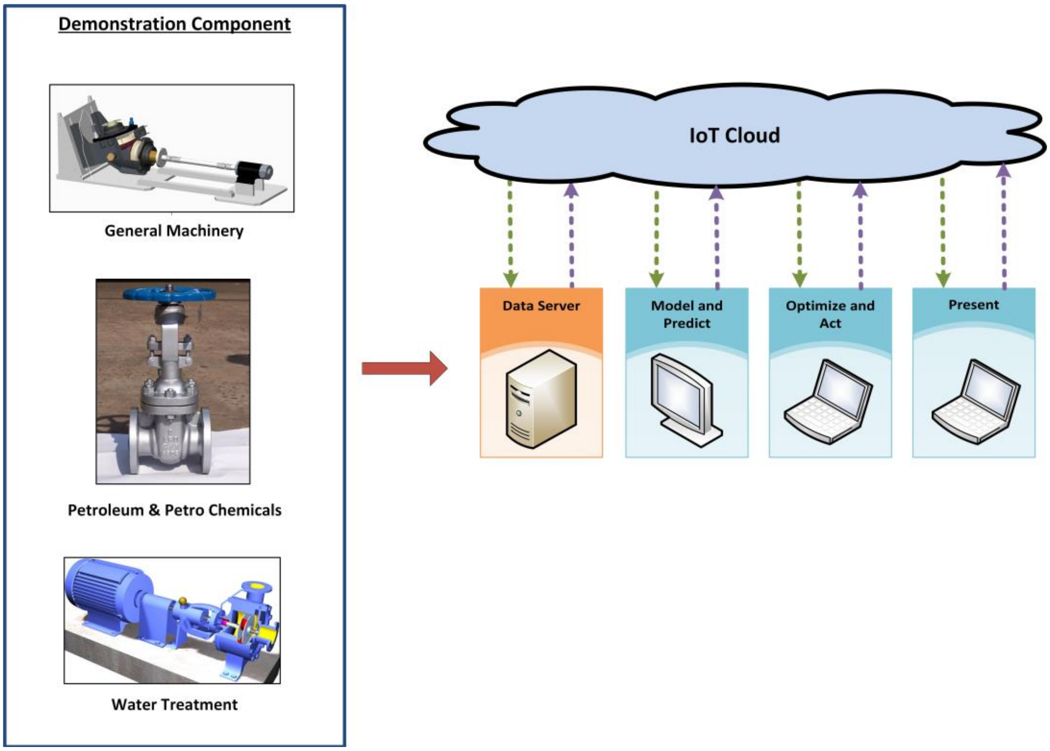

Figure 3: Internet of Things demonstration setup for various industries using different components.

5.1 General Machinery

Industries related to general machinery include aviation, aerospace, steel industries, paper industries, and other heavy industries. These industries have a lot of maintenance issues related to gears, bearings, shafts, and structure. Previously, these industries have relied on a preventive maintenance strategy based on time. Due to this, maintenance is one of the largest cost drives in these industries with maintenance representing up to 60% of total costs [Mobley, 2002]. Implementing predictive maintenance would help to reduce these costs by decreasing the amount of unnecessary repairs. A demonstration for predictive maintenance in general machinery has been created using a gearbox, shown in Figure 3 [Edwards et al., 2016]. Rotating components are heavily used in general machinery, and a gearbox is a good example.

5.2 Petroleum and Petro Chemicals

Industries related to this area include energy, gas, oil, and nuclear. The products of this industry provide many of the needed materials for our daily lives from propane to nuclear energy. This area is also experiencing a large growth and with that an increase in maintenance needs. Implementing predictive maintenance can help to address the maintenance issues this industry will face while reducing cost. Two problematic areas in this industry are control valves and process automation. A demonstration related to this industry could be built around a control valve, shown in Figure 3. The control valve would be fitted with various types of sensors. The goal of this demonstration would be to train and educate users on new monitoring techniques and how they could benefit their company. Similar to the demonstration for general machinery, there will be three screens for the user to view during the demonstration. The user will be able to see on the screens how different monitoring techniques can improve the data collected and provide more accurate models.

5.3 Water Treatment

The desalination and purification of water is becoming a more pressing issue as the human population increases and water resources decrease. Water desalination has the potential to be a solution to water shortage problems, but currently it is a very expensive process. Establishing a predictive maintenance program can help to reduce some of these costs by reducing unnecessary downtimes and increasing reliability and availability. For this demonstration, a pump will be used to demonstrate predictive maintenance, shown in Figure 3. Sensors will be used to monitor pressure, temperature, and motor amperage. The goal of this demonstration will be to show how predictive maintenance can ensure that unscheduled maintenance is not a part of the high cost of water desalination. This demonstration would be similar to the setup of the general machinery demonstration.

5.4 Results

The gearbox demonstration for general machinery has already been implemented by the Center for Predictive Maintenance. Demonstrations for other industries would be very similar with just the component being monitored changing. The gearbox is fitted with various sensors to collect data for temperature and vibration. Data collection software would then be used to transfer the sensor data to be stored in a database where historical data has already been processed. During the demonstration, users will see three screens. The first represents the “data collection and integration” step. The users will see how the data looks coming off the gearbox and visualize any trends. The “model and predict” step is not visible to users by itself because it’s mostly calculations, but the user can get an understanding of this step by observing what happens before and after this step. The “model and predict” step will take in the data being collected and run it against created fault models. The output of this step will be visible in the next screen which shows the output of the models. The second screen represents the “optimize and act” step and will display work-order generation based on the results from the predictive models. The last screen represents the “present” step and displays a dashboard that shows the real-time condition of the gearbox. The demonstration is designed to allow faults to be introduced.

Figure 4 shows example screenshots of what the audience sees during the demonstration. The top row represents views during normal operating conditions. In screen one the audience can see the values for different sensor readings. During normal operating conditions nothing unusual is noted. The data is continuously being compared against the fault models and outputs the results to screen two. Since there is no fault being detected, the bottom portion of the work order is empty. Screen three represents a real-time dashboard that shows the user the health condition of the gearbox. The health condition reads normal since there is no fault. The bottom row represents what an audience sees when there is a fault detected. During the demonstration, a fault will be introduced. In this example it is a thermal fault. In screen one, the audience will see the temperature readings start to rise compared to when the gearbox was running normally. The fault models will now detect that there is a thermal fault based off of the new data. Screen two will then create a work order based on a thermal fault and the bottom section will be filled out with instructions. Screen three will also be updated and the dashboard will show the health condition as being critical, alerting the user that something is wrong. This setup allows the audience to watch all three screens change as the condition of the component changes.

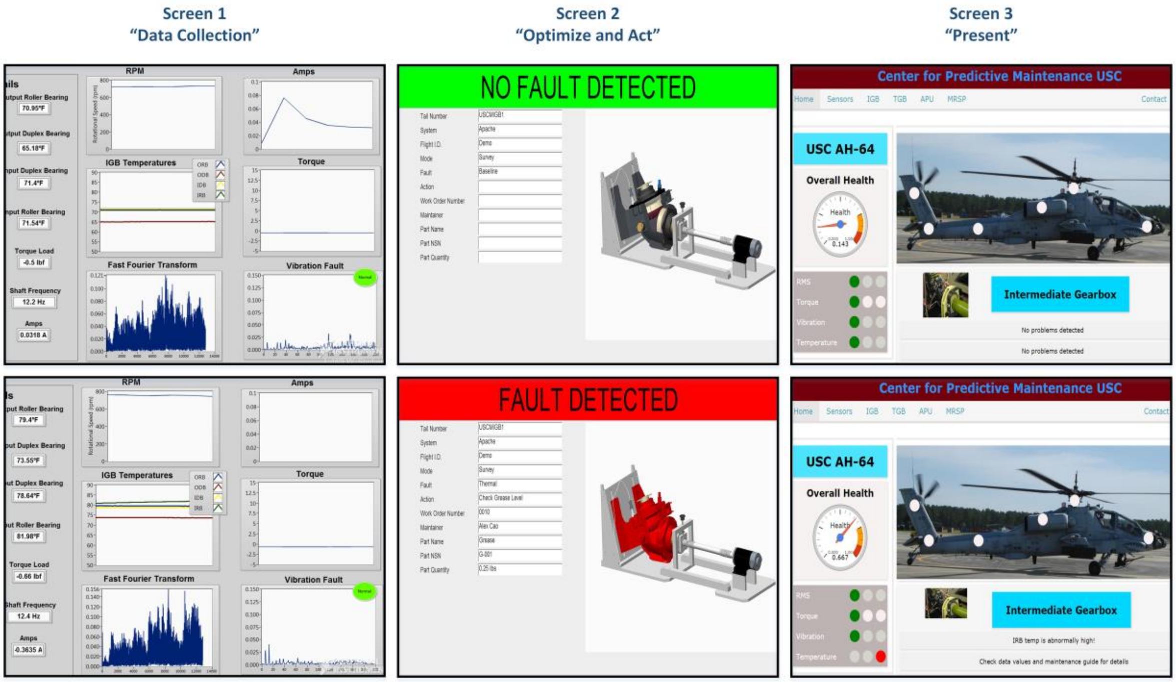

Figure 4: Screenshots of what the audience sees during the demonstration.

6. Conclusions

With the advancement of technologies such as big data analytics and cloud computing, IoT has continued to grow and change the way users collect, view, and analyse data. Using an IoT approach in maintenance can help industries move to predictive maintenance which is the optimal maintenance strategy. Predictive maintenance relies heavily on data, and IoT provides the best methodology for analysing data and connecting all users. The demonstrations previously outlined are built on an IoT methodology for predictive maintenance that can be applied to any industry's maintenance needs.

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