Predictive maintenance format pdf

Predictive maintenance (PdM) is a type of condition-based treatment that monitors the condition of assets using sensor devices. These sensor devices supply data in real-time, which is used to predict when assets will require maintenance and prevent equipment failure. How predictive maintenance compares to other predictive maintenance (PdM) options is the most advanced type of maintenance currently available. With time-based maintenance, organizations risk doing too much maintenance or not doing enough. And with reactive maintenance, maintenance is performed when needed, but at an unscheduled downtime cost. Predictive maintenance resolves this issue. Maintenance is only scheduled when certain conditions are met and before the asset is damaged. A brief history of predictive maintenance organizations began using predictive maintenance tools around the beginning of the twenty-first century. To monitor asset conditions, organizations use periodic or offline approaches. A study documenting three PDM case studies from 2001 states: Vibration measurements are taken periodically —once per month in general—and vibrations are monitored by comparing previous measurements with new one. Currently, a sustainable or online approach is used to monitor asset conditions. Remote monitoring is also possible by connecting IoT sensor devices to maintenance software. When certain conditions are met, a work order for inspection is triggered. How does predictive maintenance work? The first step in practicing predictive maintenance is to build a baseline. You need to monitor the conditional base of assets and collect data before installing sensors. That way, when you start collecting conditional data, there are controls to compare any abnormalities. From there, it's simple - whenever a piece of equipment performs outside normal parameters, the sensor triggers your predictive maintenance protocol. Typically, work orders are generated in your CMMS and assigned to technicians so that they can perform the necessary repairs to address the Predictive Maintenance Workflow Anomaly Graph below outlining predictive maintenance workflows from start to finish. The ultimate goal with predictive maintenance is to capture the damage before it occurs by monitoring the condition of the equipment. Note: Example predictive maintenance workflow How to implement predictive maintenance Before predictive maintenance is applied on the facility floor, the ROI case is presented to management. Maintenance staff and machine operators are also trained by using PDM technology. Once this happens, the true implementation begins. 1. Create a baseline Maintenance team setting acceptable condition limits for assets that will have sensors. 2. Install the relevant Internet of Things (IoT) Sensor device affixed to the asset. For example, the attached to mechanical assets with gears and temperature sensors attached to the 3. Connect the device to the IoT Software connected to the CMMS or remote dashboard where the data is collected and analyzed. 4. Schedule maintenance checks are automatically triggered by CMMS when the condition limit is exceeded or the person who monitors the dashboard schedules the check manually. Different types of IoT Sensors by Monnit Predictive maintenance type Vibration Analysis Machine Speed: High | Machine Type: Mechanical | Cost: Medium This is a type of analysis for predictive maintenance inside manufacturing plants with high spinning machines. Since there has been longer than other types of monitoring conditions, it is relatively cost-effective. In addition to detecting looseness as in the example above, vibration analysis can also find imbalances, misal alignment, and bearing wear. Note: Using vibration analysis in predictive maintenance at Motor Engine Speed: Low, High | Machine Type: Mechanical | Cost: Low This type of analysis requires less money to be implemented and used for low and high spinning machines. It is very popular among lubrication technicians. According to an article by Machinery Lubrication, acoustic analysis is similar to vibration analysis; however, the focus is not to detect the cause of the spinning equipment failure by measuring and monitoring vibrations at discrete frequencies and recording data for trending purposes. Instead, acoustic bearing analysis is aimed at lubrication technicians and focuses on proactive lubrication measures. Acoustic Analysis (ultrasonic) Machine Speed: Low, High | Machine Type: Mechanical, Electrical | Cost: High While sonic acoustic analysis borders on proactive and predictive maintenance lines, ultrasonic acoustic analysis is only used for predictive maintenance efforts. And because it can identify sounds associated with machine friction and stress in the ultrasonic range, it is used for electrical equipment that emits finer sounds as well as mechanical equipment. It says that this type of analysis predicts imminent damage better than vibration or oil analysis. Infrared Analysis Engine Speed: Low, High | Machine Type: Mechanical, Electrical | Cost: Low Type analysis is not dependent on rotation speed or hard assets. It is therefore suitable for different types of assets. When temperature is a good indicator of a potential problem, infrared analysis is the most cost-effective tool for predictive maintenance. It is often used to identify problems associated with cooling, airflow, and even motor stress. Predictive maintenance example A centrifugal pump motor at a coal preparation plant is a vital asset for daily operations. To prevent unscheduled downtime, the maintenance team decided to use predictive maintenance technology. Because this is a great piece of mechanical equipment doing heavy rotation, the obvious option is to monitor vibrations with a vibration meter. The team attaches attaches the meter is close to the inner bearing of the pump and sets the normal base measurement, visualized through a waveform graph (below, left). A few months later, the vibration meter identifies the acceleration spike (below, right). The maintenance team remotely reviews this new data and schedules inspections. Technicians who carried out the inspection found loose ball bearings and fixed them. Going forward, the team connects the vibration gauge to its CMMS. Now, when the same spike is identified, errors with ball bearings are predicted and work orders are automatically triggered to make repairs. Note: This example was inspired by the real use cases documented in this study. Predictive maintenance benefits Predictive maintenance stands to improve your overall maintenance and reliability programs. By using technology and best practices to streamline processes and increase productivity. Some of the main benefits of predictive maintenance are: Increase asset uptime by 30% and reduce unexpected failures by 55%. Streamline maintenance costs through reduced labor, equipment, and inventory costs. Improve safety. PREDICTIVE MAINTENANCE ROI According to a paper by the U.S. Department of Energy, a well-researched predictive maintenance program will all but eliminate catastrophic equipment failures. Compared to preventive maintenance programs, cost savings are 8 to 12 percent higher; and compared to reactive maintenance programs, cost savings range from 30 to 40 percent. Other figures stated by the Department of Energy include: Return on investment: 10 times Maintenance cost reduction: 25% to 30% Elimination breakdown: 70% to 75% Downtime reduction: 35% to 45% Production increase: 20% to 25% Note: Increase production by 25% by reducing downtime, details and maintenance costs Predictive Maintenance Severance not for any organization, especially those that have not implemented planned maintenance activities. But for larger organizations that have surpassed traditional PM's and have additional budgets, predictive maintenance can provide roi that turns maintenance departments into higher sources of cost savings and profits. This template demonstrates how to create and use predictive maintenance models to predict asset failures. Predictive maintenance covers a variety of topics, including but not limited to: failure prediction, failure diagnosis (root cause analysis), failure detection, failure type classification, and recommendation of mitigation or maintenance measures after failure. As part of its Azure Machine Learning offering, Microsoft provides templates that help data scientists easily build and implement predictive maintenance solutions. ** This predictive maintenance focuses on techniques used to predict when machines in the service will fail, so maintenance can be planned in advance.** The template includes a preconfigured set of machine learning modules, such as such as as a custom R script in the *Execute R Script* module, to enable end-to-end solutions from data processing to machine learning model deployment. Three modeling solutions are provided in this template to complete the following tasks. - Regression:** Predicting Useful Life Time (RUL), or Time to Fail (TTF). - Binary classification:** Predict whether an asset will fail within a certain time frame (e.g. days). - **Multi-class classification:** Predict whether an asset will fail in a different time window: For example, it fails in the [1, *w0*] day window; failed in window [*w0*+1,*w1*] day; not fail within *w1* the day of the time unit mentioned above may be replaced with working hours, cycles, mileage, transactions, etc. based on the actual scenario. This template uses simulated examples of aircraft engine run-to-failure events to demonstrate the predictive maintenance modeling process. The implicit assumption of data modeling as done below is that the in-demand asset has an advanced degradation pattern, which is reflected in the measurement of asset sensors. By examining the value of asset sensors over time, machine learning algorithms can learn the relationship between sensor values and sensor value changes to historical failures to predict future failures. We recommend checking the data format and going through all three template steps before replacing the data with your own. The template is divided into 3 separate steps with a total of 7 experiments, where the first step has 1 experiment, and the other two steps each contain 3 experiments that each discuss one of the modeling solutions. ! [Workflow] (stream](