Industry 4.0 for Aerospace Manufacturing: Condition Based Maintenance Methodology, Implementation and Challenges

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ABSTRACT

Industry 4.0 (I4.0) is the fourth industrial revolution where operations are linked through data generated by machines. I4.0 involves production ecosystems where operations are monitored, recorded, and analyzed for use in widely interconnected and automated activities. This can be performed at Edge or Cloud[1] levels. In the industrial big data era, with ever maturing sensor technologies, data capture, communication, and storage technologies, utilizing machine data for operational insights provides companies with competitive advantage. These can increase cost savings for operation and maintenance, reduce or even eliminate unscheduled downtime and / or ensure on-time delivery of products. In this work, we will cover a methodology for condition-based maintenance (CBM) at aerospace manufacturing facilities. The methodology includes sensor selection, data collection, transmission, storage, return on investment for CBM, and building CBM models for detection. We will delve into challenges of implementing this methodology in industrial settings by covering planning, technology insertion, logistics, and decision-making.

1. INTRODUCTION

With the advent of Industry 4.0 (I4.0) and advancement in digital transformation, manufacturing facilities are embarking on the journey of transforming operations with big data. Initial efforts started with measuring operational efficiencies with standard metrics like overall equipment effectiveness (OEE). The operational drive behind improvement of OEE is to reduce machine breakdowns and malfunctions.

Condition-based maintenance (CBM) has proven its value in addressing root causes on the machine level to improve operational metrics like OEE. To implement a CBM program, the common practice is to start with a pilot project as a proof of concept. Success of the pilot project drives the decision in rolling out the technology in a larger scale.

In this work, we discuss the milestones of implementing a CBM program at one of our aerospace manufacturing facilities. We will go over the methodology developed for identifying CBM candidates, building CBM models, deploying and scaling a CBM programs, and evaluating return on investment.

2. APPROACH

Bringing a facility up to I4.0 standards requires continuous operational data collection from machines. Once the data is available, it can be used for various applications such as descriptive, diagnostic, and predictive analytics. In order to empower applications such as predictive maintenance, several steps must be taken. Figure **1** shows different phases of a methodology that will result in improved predictive maintenance capabilities in a facility. It is important to point out that the outcome of some of the tasks outlined in Figure **1** contribute to other aspects of I4.0 efforts as well and not only the predictive maintenance.

In Phase 1, we identify critical parts and machines; select sensors and a data collection strategy; and build data collection infrastructure. These three steps allow for the generalization of data production practices applicable to a variety of applications. The data can later be used for CBM, simple visualizations, status monitoring, etc.

Phase 2 involves utilization of the data. It starts with selecting visualization and business intelligence tools that help the operation excellence goals. Predictive maintenance model building, selection, and evaluation fall under this phase. Successful outcomes are tied to a proof-of-concept to get buy-in from stakeholders and senior leadership within an organization. Once CBM feasibility is proven, the proof-of-

[1] Cloud computing refers to using computation power in remote servers and usually involves the services provided one of the commercial vendors in this space. Edge computing refers to localized computing power on site usually using hardware exclusively designed to perform such computations.

concept is evaluated for its applicability to scale to the entire facility (and other similar facilities).

Phase 3 covers the model deployment and consumption. In this phase CBM models are scaled and rolled out to the entire facility. Model consumption decisions are made at this stage. For example, how users consume the model (on-demand vs. on schedule), what sort of alerts the system generates, how users interact with alerts and take actions on them.

We will go over these steps in more details in the following sections.

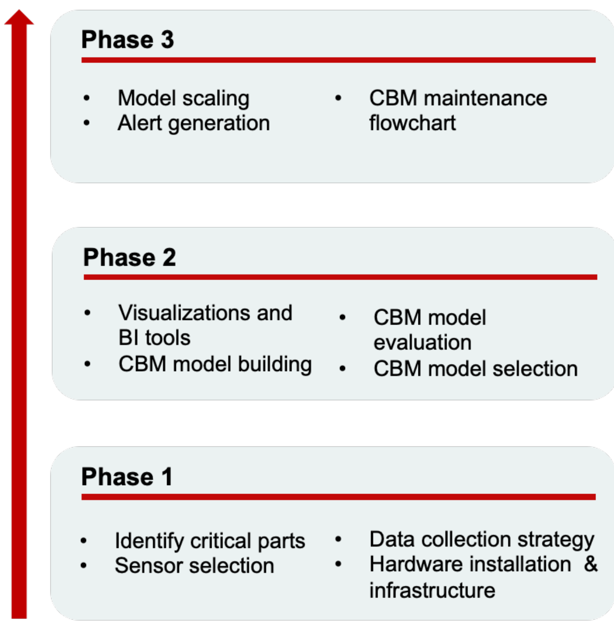

Figure 1- CBM implementation approach (BI: business intelligence)

3. BUILDING UP DATA INFRASTRUCTURE

This stage of work focuses on building up the data collection infrastructure for predictive maintenance.

3.1. Identifying Critical Parts

A wide variety of equipment are involved during different stages of a product's manufacturing process; however, it is not practical to monitor every type of equipment. Each equipment type tends to have different performance baselines based on its utilization and nature of the machine operations. Taking aerospace manufacturing as an example, machine tools, grinders, measurement equipment, etc. work concurrently to produce and examine parts. It is widely acknowledged that machine tools are the most critical assets among others given the variety of tasks they perform and their high utilization rates. Certain machine tools run 24/7 with limited backup capacity. Therefore, it is necessary to focus on the critical assets to determine CBM feasibility.

Some equipment (such as machine tools) have a low failure rate, but the consequences of failure are expensive; for example, long downtimes, expensive scrap costs and sometimes collateral damage. On the other hand, some equipment have a high failure rate, but the failure consequences are not as severe. Cooling pumps are a good example of such equipment.

3.1.1. Sources of Information

It is critical for manufacturing facilities to keep detailed maintenance records; these present opportunities for practitioners to understand factory performances, drill into details for downtime and make data-driven improvement decisions. (Fleischer et al., 2009) conducted a study to reveal the top four major assembly components in machine tools. The paper concluded that drive axes malfunction caused 38% of machine tool breakdown and spindle and tool changer issues constituted 26%. While the statistics may differ across industries, studies like this serve as good reference for CBM practitioners to conduct similar studies reflecting the ground truth for root causes behind machine downtime.

Technical insights from existing maintenance programs and subject matter experts are another source of information. CBM is a fundamental step to move from corrective and preventive maintenance to the predictive maintenance space. Technical insights are already built into existing maintenance programs. For example, for failures associated with high cost and severe consequences, preventive maintenance programs are normally in place to check specific components at fixed intervals. This helps the maintenance team to stay informed of the machine conditions at fixed time intervals and allows them to arrange maintenance prior to breakdowns. Components associated with these failures are great CBM candidates. Corrective maintenance generally addresses failures with lower consequences. However, depending on failure frequency and resulted downtime, failures that are currently addressed through corrective maintenance can also be potential CBM candidates.

3.2. Sensor Selection

In industrial applications, it is critical that due diligence, research, and even experiments are done to select the right sensors. At the end of the day, the model is as good as the data that feeds into it.

Different sensor types including vibration, temperature, acoustic emission, electric current, etc. have been used for monitoring component performances. (Yu, 2012) used acoustic emission, vibration, and motor current sensors with 250 Hz sampling rate and 9000 points per sampling for an experimental setup to evaluate cutting tool conditions. (Schmidt & Wang, 2018) used measurement data from Renishaw QC20-W measuring device which performs the well-established double ball-bar measurements on linear axes. This test was designed to run offline for multiple purposes including estimation of machine part accuracy, source of deviation as well as predictive maintenance.

Past literature and similar case studies serve as references for specific monitoring decisions. The fundamental questions are:

1. How will the CBM candidate manifest its failure and degradation signatures?
2. Are the sensors under consideration able to capture the above signature?

Take bearing faults on the machine tools for an example: if there is a damage on the inner race of a rolling element bearing, its impact will show up every time there is a physical contact between the roller and the damaged area (Rastegari et al., 2017). Therefore, given a reasonably high sampling rate that is at least twice the maximum frequency in the vibration signal, the frequency spectrum will display increased vibration around Ball Pass Frequency Inner Race (BPFI), which is in general not the harmonics of the shaft turning speed. This provides guidance for sensor selection and choosing vibration sensors that can collect data at desired resolutions. However, if the end goal is not detecting failures at the bearing level but rather detecting general issues with the machine tools, more generic vibration techniques can be applied. This changes the requirements on sensor resolution. For example, in the work of (Rastegari et al., 2017), broadband vibration is measured to monitor spindle unit vibration level over time by following Swedish standard for machine tool spindle vibrations using sensors installed on spindle housing.

Machine tools come with internal sensors that can be leveraged. One of the challenges with such sensors is their default location. Usually, they are not installed on locations where fault develops and subsequently are indirect measurements of machine conditions. In many cases, they are not collecting data relevant to specific CBM needs.

As an example, in one of our facilities, some of the newer CNC machines come with temperature and electric current sensors. Data from these sensors as well as other information such as rotational speed of tools and tables, axis location, motor temperature, etc. could provide a baseline for predictive models. However, to monitor the degradation of critical parts in these machines, we need vibration data, which is not available.

Installing additional sensors at desired locations provide the option of selecting sensors according to monitoring targets and generating more accurate measurements. However, this requires additional cost and domain expertise with increased technical complexity. So extra sensors must be justified to the stakeholders.

To install 3rd party sensors, they must be able to meet several requirements:

- Output parameters: whether it is only vibration, or other signals as well. Is the output the amplitude of the signals or they are derived parameters?
- Sampling frequencies: what is the highest sampling frequency that the sensor can provide?
- Signal processing functionalities: does the sensor have denoising filters in various frequencies?
- Environmental conditions: some of these sensors are installed in harsh environments with high temperature or high humidity or both.
- Cyber security: the sensor must be able to meet the cyber security requirements of the company.

Process data and product measurement data are another source of information for CBM purposes. This is because of the product requirements and the correlation between machine degradation and the product parameters that are measured. For example, (Tong et al., 2017) used product quality measurements to detect anomalies in a multistage manufacturing environment.

3.3. Hardware installation and infrastructure

Once the correct sensors are selected, they need to be installed. The placement of the sensors is a crucial decision. For example, for vibration sensors, they must be in a place where they sense the vibration of the component of interest and to some extent be isolated from other components. Vibration is measured in three directions (X, Y, Z or horizontal, vertical, and axial). Some sensors can measure all three and some can measure only one or two. It is important to pay attention to the direction while setting up the sensor.

Sensors are controlled by programmable logic controller (PLC). Usually, sensor vendors sell a package that includes a certain number of sensors and their PLC. The sensor installation and PLC installation require electrical wiring that may need to meet some standards that are implemented in the facility.

Machines with built in sensors have various types of controllers. 3rd party sensors have their own connection protocols as well. The challenge is to collect data from all these different devices that use all different languages and protocols. This can be done with commercially available industrial software or communication platform that can standardize the connectivity between all the machines in a manufacturing facility. This platform then connects to a database and feeds the sensor data into the data storage. These platforms are highly customizable in terms of data collection frequencies, which parameters to collect, etc. They can be set to continuously collect data or be triggered by some sort of an event or a program on a machine.

There are various options for data storage. Some may use an on-premises server. The advantage of having such data storage is the cost, which is mostly a one-time payment with negligible maintenance costs. However, such storage options have limited capacity and can become a bottleneck for scaling the data collection efforts. A solution is to use cloud data warehouses where the set-up cost is low, and scalability is easy. However, the total cost of operations could easily add up as the storage costs do not move linearly with storage used (and in some cases the cloud vendor's accounting practices are vague).

3.4. Data Collection Frequency

Data sampling frequency is a critical aspect of modeling and affects the model choices substantially. Ideally, engineers require signal data with high frequency sampling rate where the rate is twice as much as the highest frequency in the machine (referred to as Nyquist rate). Data collected with such frequency allows the engineers to use various signal processing techniques and analyze the frequencies where degradation manifest itself. However, this is easier said than done.

In a large facility with hundreds of connected machines, multiple sensors on each machines collecting data 24/7, sampling frequencies in the range of 10s of kHz create vast amounts of data. This will substantially affect the data warehousing costs of a facility as well as data processing and computation needs.

As discussed earlier, predictive maintenance is not the sole goal of connected factory. It falls under the broader goal of operation excellence and effectiveness. To achieve this goal the data needs to be consumable to non-experts mostly in form of business intelligence tools. Signal data with high frequency sampling rates are covered with noise and are not readable without any additional post processing. So there exists a balance for all the different users' needs. On one hand engineers want high frequency signal data while on the other hand the shop floor and industrial engineers want data that needs the least amounts of post processing.

There are ways to address these issues. One is to lower sampling frequency to once every few minutes and collect data that are more like parameters of the signal (e.g., rms, crest, kurtosis) rather than the actual waveform with lots of noise. A lot of sensors offer such parameters. This way the data is useable in BI (Business Intelligence) tools with minimal post processing effort. The storage costs will be manageable as well. However, this will make the job of predictive maintenance engineers challenging. The modeling options will be completely different than the ones with high frequency waveform signals.

A challenge with low sampling frequency data is the machine tool programs. Think of a program as something that builds a specific piece of a part. To build a whole part, the machine tool must go through several programs. These programs can be as short as few seconds but can go on for several minutes. A low sampling frequency collects data in the middle of a short program and in many scenarios, it is not clear if the data is showing an anomalous behavior or just catching normal fluctuations due to program changes.

Knowing all perks and downsides of various data collection strategies, a middle ground can be achieved. For some equipment such as pumps with minimal program changes, low frequency sampling data collection is desirable. Especially since there are many of such equipment in a facility and they run pretty much nonstop.

For machine tools with various programs, the sampling frequency must be high. However, it does not have to be a continuous 24/7 data collection. The data collection could be done during a specific program that is common among all the machines. The warmup program is a good example of such programs. Every machine tool must go through a warm-up program, and it usually lasts a few minutes. The warm-up program can provide a unified condition for all the machines in the facility. An option is to collect data only during warm up with very high frequency. This should provide enough good data for a CBM analysis while keeping the data storage capacity in check. Table **1** summarizes the benefits and downsides of each data collection strategy.

Table 1- Characteristics of each data collection approach

	High Frequency Data Collection	Low Frequency Data Collection
Collected data	Waveform	Parameters (rms, etc.)
Sampling rate	On a scale of kHz	On a scale of min
Collection period	Few minutes a day	24/7
Data noise	High	Low
Storage needs	High (if collection period is long)	Low
Best application	CBM	BI
Machine operation programs	Many	Few
Best for equipment	Machine tools	Pumps, blowers, etc.

4. MODEL DEVELOPMENT

CBM model development involves various steps such as defining requirements for model outputs, evaluating data resources, selecting or developing models based on requirements and data resources, validating model performance, and incorporating plans for field-enabled model improvements. Figure **2** summarizes the flowchart of this process.

Several options could constitute as outputs for CBM models: estimation of remaining useful life, probability of component failure, indication of specific failure mode, feature contributions to estimation metrics etc.

Evaluating data resources and the available sensor data, in conjunction with other sources of information such as process data, failure records, and other meta data affect the model development options. This information combined with the required model outputs dictate the CBM model development and selection.

Depending on the availability of failure data and preferred alerting methods, CBM models can be supervised or unsupervised. Lacking historical failure records puts a restriction on using supervised models. However, if domain knowledge or similar case studies have provided insights on potential failure signatures in data, supervised model can still be applied through failure data simulation. Models that indicate specific failure mode require either failure data of interest or built-in physical insights from domain knowledge. For example, increased vibration at the frequencies of interest indicates specific failure mode of a component.

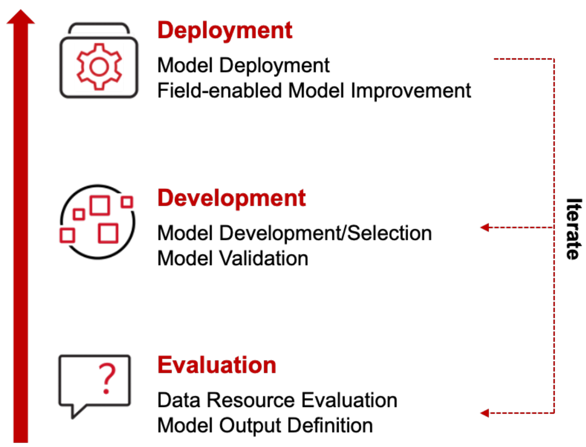

Figure 2- CBM Model Development Process

Data resource evaluation process includes gathering past failure records, confirming availability of corresponding sensor data before and after failure for event validation, as well as collecting healthy data for training and evaluation of false alarms.

As an example of previous studies in this domain, (Schmidt & Wang, 2018) studied 4 years of data from 29 multipurpose machine tools with 32 instances of ball-screw failures under real manufacturing settings. They explored preprocessing methods such as Principal Component Analysis, Statistical Feature Selection, Independent Component Analysis and Correlation-based Feature Selection prior to feeding data into classification models. Then, they used methods discussed by (Kiang, 2003) such as K-nearest neighbors, Back-propagation Feed-forward Neural Network, Decision Trees, Naïve Bayesian, Random Forest, and Support Vector Machine. The combination of processing and classification method yielding the highest accuracy was chosen to assess economic benefit of predictive maintenance. (Rastegari et al., 2017) experimented evaluating the trend of spindle vibration data under different operating conditions. It proved to be effective in capturing bearing failures given specific machine operating regimes. This method is commonly used in industry by utilizing well-established failure thresholds. (Chen et al., 2020) applied Stacked Autoencoders for anomaly detection of semiconductor manufacturing process which is another option for unsupervised learning. (Saci et al., 2021) designed a low-complexity anomaly detection algorithm by modeling distributions of the healthy processes and detecting anomalies based on thresholds for probability density function. The method is tested using a practical dataset from industrial steelmaking furnaces operation and it outperforms support vector machine and random forest algorithms in most performance metrics with improved computational efficiency.

Scarce failure data is a common challenge in aerospace manufacturing settings. This is due to various reasons, failures for critical equipment are mostly prevented through frequent scheduled maintenances, equipment may not have been connected in the past, or there is no established process to capture and label historical failure data. For large enterprises seeking to roll out CBM capabilities across multiple sites, unsupervised model is beneficial. These models can be directly applied to newly connected equipment where there is only normal operation data. It also helps in scenarios where data for historical failures are not available.

Existing models can be selected, or new models can be built if existing ones do not satisfy requirements on model output or performance expectations. Aspects to consider include model performance, computation requirements, interpretability, and alignment with performance expectations.

Failure signature analysis using historical data or domain expert analysis on potential failure symptoms, are great ways to enable insights for model selection and building. Visualizing the failure data and extracting features to reveal potential failure signatures is important. Identifying failure signature in the data (whether raw data or feature engineered data) can help with validating that CBM models are effective and are capturing failure or degradation signatures.

Some CBM models are effective in capturing abnormal values, but some can capture gradually developing trends as well. Ideally, one or a suite of models that can capture different types of failure signatures is desired.

Model validation can be achieved with historical failure data or simulated failure data if the former is not available at the development phase. Validation metrics can include standard machine learning evaluation metrics like confusion matrix or modified metrics that satisfy specific project requirements. Modeling results should be reviewed with both stakeholders and model consumers to make sure the outputs are practical. This means that there is enough lead time for factories to plan maintenance ahead of time, catch critical failures, order spare parts and reduce false alarms. Successful execution of this process will contribute to improved user trust in the technology and the transition of technology ownership from the model development team to the technology user team.

Lastly, once CBM models are validated and ready for deployment, consider extending the model development into field deployment. It is worth planning for model enhancement enabled by both user feedbacks and more available data resources down the road. Once a manufacturing site is CBM enabled, more failure data becomes available over the years after model deployment. Existing models can be enhanced or even replaced with insights from new data and additional analysis.

5. MODEL DEPLOYMENT

Model deployment requirements is a joint effort between the development team and the stakeholders. Specifics about the output requirements, model running cadence (on-demand vs. scheduled), computational resources, deployment environments and other aspects of deployment solution should be discussed in this phase.

Models could be consumed by various types of users with different goals in mind. For example, factory floor supervisors may prefer to have model outputs on a dashboard where it's easier to digest and act on the information. Digital leads on the factory floor want high-level metrics in report format delivered through email on a regular cadence or alternatively accessible via an online platform that may or may not be a part of the deployment platform. A technical workshop with the users is a great way to discuss and gather deployment requirements.

The deployment solution should be flexible and efficient in the following aspects: incorporating user inputs, retraining deployed models, monitoring data drift (if not built in the CBM model itself), and integrating capabilities with other processes within the organization.

User input can include but not limited to feedbacks related to model accuracies (upon failure occurrences), pre-defined user modifications (for example, threshold adjustment based on post-deployment experiences, disabling alerting functionalities due to unexpected false alarms) and potential functionality expansions in the future once the process matures with more desired user inputs that are not initially defined.

Models should be retrained upon events that may cause major shift in data input. These events can range from performed maintenance, sensor adjustment, to equipment upgrade etc. If data drift capability is available, model retrain can also be enabled automatically once drift is detected and training data becomes available.

With a wide variety of tools offered by today's marketplace, model deployment can be performed on an end-to-end platform, or a platform dedicated for deployment. In the latter case, integration capability with other platforms that are currently used or being planned on the organization's digital roadmaps should be considered. This is especially critical for large organizations where the application of CBM technology occurs across a high number of facilities and business units and the cost and complexity of platform switch is high.

6. RETURN ON INVESTMENT

Performing a return on investment (ROI) analysis prior to CBM implementation is a good practice to put dollar numbers on the value of the CBM implementation.

ROI calculation require inputs from the previous sections discussed here, however, some inputs are clearer than the others. For example, historical failure can provide an estimate of parts' reliability. It is also possible to get reliability estimation of some common components from the literature. This becomes more ambiguous for parameters related to model accuracy. If the models are being built from the grounds up, their performance is unknown. Even for reusing the same models in new facilities, depending on the data and unique problems facing the facility, the model performance could vary. To capture such uncertainties, we use probability distributions for various. For example, Figure 3 shows a triangular distribution that models the number of false positives a predictive model can generate in a year per equipment. Here, it's assumed that a facility with 100 machines, there are on average 3 false positives per year (the mode of the distribution).

All in all, this requires the ROI analysis to account for the uncertainty that comes with the input parameters given to a model. Stochastic discrete event simulation is a good methodology that provides the tools needed to account for such uncertainties. Events are failures and maintenance that change the state of the system. These events occur in discrete segments of time, and they have uncertainty associated with their occurrence. Each event has a cost associated with it, which again has uncertainties. The details of how to do such analysis can be found in the works of (Bakhshi & Sandborn, 2017).

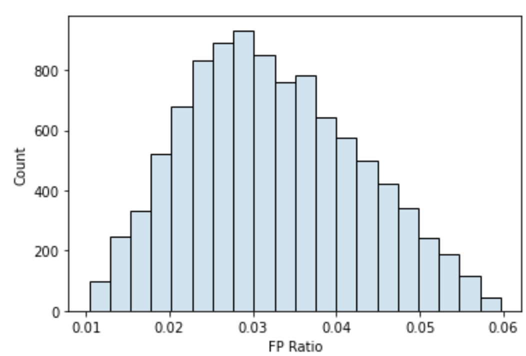

Figure 3- Number of false positives per year per equipment.

We performed such analysis for one of our aerospace manufacturing facilities. In this facility the main cost drivers that justify CBM are costs of scraping the parts that were being built when a machine failed as well as costs of delaying a delivery of the parts. Other costs factors were value of downtime (both maintenance and lack of spare part availability) and the cost of maintenance personnel who perform the corrective maintenance action. These are cost avoidances that highlight the benefits of having a CBM solution in place.

In terms of CBM costs, there are costs of sensor hardware and their installation as well as recurring costs of data warehouse and model deployment infrastructure. However, the main cost driver is the model development costs, which requires a dedicated data science team. The model development cost is a one-time cost.

Using Monte Carlo analysis, we were able to generate distributions for expected ROI values of implementing CBM in this facility. Figure 4Figure **4** shows the ROI distribution for the fifth year after implementation of CBM.

It can be seen that after 5 years, the expected average return is about 7 times the investment made over time (mode of the distribution).

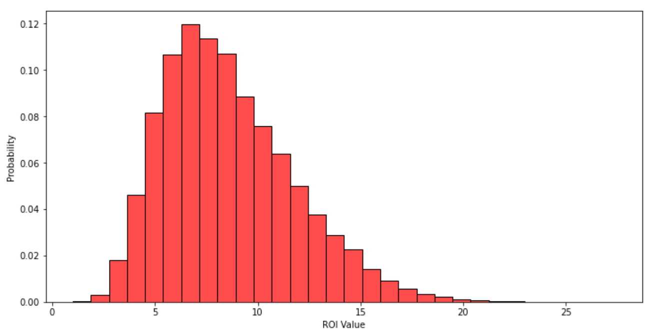

Figure 4 - ROI distribution for year 5 of implementing CBM

7. CHALLENGES

There are several challenges in developing, implementation and maintaining CBM solutions in industrial settings. Here, we briefly discuss some of those.

7.1. Maintenance Records

Earlier in section 3.1.1 we referred to maintenance logs as a source for identifying machine breakdowns. ERP systems are widely available at manufacturing facilities for a variety of applications including but not limited to maintenance logs. Historical maintenance data with all their detailed information exist in the ERP system. The information is human text typed into the system, with all the common issues that come with human entered text (typos, etc.). To develop CBM models, we look for historical failures in the facility and once we identify them, we can bridge the records with the data. To identify historical failures, we look them up in the ERP system. However, many ERP systems have limited search capacity due to the nature of those systems. The current practice is to just look up keywords and narrow down the results using some filters. This is not only a cumbersome manual task, but also susceptible to all the issues that come with text data such as typos. To enable automated processing of those free-text logs, the information can be exported from the ERP system to an external database where technical language processing methods (Brundage et al., 2021) can be utilized to extract information from maintenance data. This is a crucial but not so easy step in accelerating the development of CBM capabilities.

7.2. Dedicated CBM Personnel

Hardware installation discussed in section 3.3 requires dedicated staff. These are either personnel who work at the facility or a team that works for the broader organization and responsible for rolling out the capability throughout the facilities. In case it is the on-site personnel, they require training on how to implement and maintain the hardware and systems used in CBM. More than one person should be trained for each task in case a backup is needed. There are scenarios where a piece of hardware requires a reset or some trivial adjustment however the absence of the dedicated individual causes a delay or loss of data.

In case there is a central team that provides these services to a facility, then there needs to be clear instruction on how the on-site team can reach out to them when issues arise and how issues can be assigned and escalated in order to mitigate any interruption to CBM operations.

7.3. Model Maintenance

Predictive models developed and deployed for a facility must be maintained over time. There are various examples of model maintenance. Data drift is a simple example, where the data changes over time and model accuracy changes with it as well. Models need to be retrained or modified to address this issue. Another example is availability of more data (and failure events), which provide new modeling options or modifications of existing models. Overall, it is not correct to assume that once a model is developed and deployed, the job is done once and for all. It is best practice to revisit the capability every few years and update with the latest technology; for example predictive model improvements.

In developing CBM capabilities for I4.0 settings, stakeholders must account for model maintenance over time and the costs associated with it.

8. CONCLUSION

In this paper, we discussed the life cycle of developing condition-based maintenance capabilities for manufacturing facilities based on our experience of implementing such methodology at one of our company's aerospace factories. These steps include:

- Identifying critical parts as CBM candidates
- Selecting sensors and data collection frequency
- Building up the hardware infrastructure for data collection
- Develop, validate, and optimize predictive models
- Deploy, scale, and consume the predictive models

The technology readiness for CBM requires coordination from various stakeholders. These range from executives in the company to technical leads in manufacturing, on-site staff, data scientists, software and data engineers and digital technology organizations.

Model and software development aspects of CBM are only one piece of the puzzle. Building up the hardware infrastructure, prioritizing the machines and failure modes, deploying and maintaining the models over time are all critical tasks for raising the technology readiness level of manufacturing sites in regard to I4.0.

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BIOGRAPHIES

Xiaorui Tong was born in Pingliang, Gansu, China. She obtained a B.S. in Mechanical Design, Manufacturing and Automation in 2011 from Central South University in Changsha, Hunan, China, and a M.S. in Mechanical Engineering at the Center for Intelligent Maintenance Systems (a NSF Industrial/University Cooperative Research Center) in 2013 from University of Cincinnati in Cincinnati, Ohio, USA with a research focus on prognostics and health management (PHM). She received her Ph.D. in Material Science and Engineering in 2018 from West Virginia University in Morgantown, West Virginia, USA with a research focus on building computational models combining machine learning and material science principles for renewable energy applications. She worked with companies including the Goodyear Tire & Rubber Company and Parker Hannifin Corporation on developing computational models for various industrial systems. She worked at the FORCAM Inc. on enabling early Industry 4.0 capabilities for manufacturing equipment in collaboration with multiple manufacturing facilities. She is currently a senior data scientist at Raytheon Technologies and the in-house subject matter expert in PHM. Her work focuses on leveraging domain knowledge, computational modeling, and big data analytics to enable insights for industrial processes and products.

Roozbeh Bakhshi was born and raised in Iran. He attended K.N.T. University of Technology for his Bachelor's in Mechanical Engineering (2009). He holds a Masters' (2013) and Ph.D (2019) in Mechanical Engineering from University of Maryland, College Park, Center for Advanced Life Cycle Engineering (CALCE) where he was mentored by PHM Society Fellow Peter Sandborn. He has authored several scholarly articles in domains of reliability engineering, predictive maintenance, and cost modeling. Roozbeh joined United Technologies (now called Raytheon Technologies) digital accelerator in 2019 as the in-house subject matter expert in reliability engineering and predictive maintenance. His focus is on digitalizing and automating reliability engineering processes across the enterprise as well as developing predictive maintenance solutions for the hardware products that the company makes or the manufacturing equipment that build those products.