MxD Final Report 16-04-01

Achieving Smart Factory through Predictive Dynamic Scheduling	
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I. EXECUTIVE SUMMARY

Overview:

The proposed solution is aimed at dynamically scheduling maintenance opportunity windows based on the machine "health" information. Currently for existing production scheduling software, machine planned downtime is incorporated into the production schedule by time-based preventative maintenance schedules or by the experience and domain knowledge of the plant personnel. Current dynamic scheduling software systems effectively assume that the machines are 100% healthy and that similar machines do not degrade at different rates.

The proposed solution will consist of the following components to be contributed by the project proponents:

- FORCAM, Inc. Manufacturing Execution System (MES) platform and application that generates OEE metrics including dynamic scheduling application.
- Predictronics analytics-based computing engine to derive equipment health from machine data.
- Northeastern University decision support tools for production and maintenance scheduling.
- Lockheed Martin testbed machines for data source and demonstration, and domain knowledge of machine usage.

Problem Addressed:

- Current MES/OEE monitoring systems do not provide drill-down capabilities that enable end-users to investigate the condition/health of the machine so that appropriate measures can be performed to non-performing units.
- Dynamic scheduling systems allow manual inputs or time-based inputs (preventive maintenance schedules) but they do not consider the actual condition/health of the machine.
- Actions based solely on machine health metrics are difficult to justify unless they are tied to factory performance metrics such as OEE and the predictive nature of these solutions are not harnessed to its full potential unless they affect actual maintenance schedules.

Key Deliverables and Results:

The key deliverables of this project are a suite of technology and tools for dynamic scheduling of maintenance activities that combine inputs from the predictive machine health and production information, to recommend maintenance opportunities and schedules. The project developed a systematic process on how to communicate and exchange data and information among the currently disparate systems: FORCAM FORCE™ MES Platform with Dynamic Scheduling and Predictronics.

The machine/component health value and remaining useful life estimation from Predictronics are the additional inputs that are passed to the FORCAM FORCE™ MES and, in particular, are used by their dynamic production scheduling algorithm. The previously existing production schedule is a complicated optimization routine that includes information on the requested production, the expected produced material, the expected consumed material, the expected equipment production parameters (ex. machine status and shift calendars) and the available maintenance and operator plant personnel. However, instead of scheduling the downtime of machines based on the preventative maintenance schedule, the health value and remaining useful life (RUL) estimation of the machine tool components, namely the spindle and linear axis, can be used to provide a more dynamic and accurate input for the scheduling algorithm. For failure modes that have a more long-term degradation pattern, the idea would be to use the health value and RUL information to extend the preventative maintenance schedule; thus, increasing the machines availability and reducing the cost associated with labor and replacement parts. In addition, the prediction of a machine failure could be also included into the production scheduling routine in order to avoid unplanned machine failures and downtime.

Ultimately, an integrated system consisting of the different components mentioned above were deployed at the Lockheed Martin facility on four machines.

II. PROJECT DELIVERABLES

#	Deliverable Name	Description	Deliverable Type
1	Module 1: Machine Health and OEE Integration	Parsing module to catch JSON data stream from machine health system	Software
2	Module 1: Machine Health and OEE Integration	Time-similarity metrics to relate OEE events and machine health trend	Software
3	Module 1: Machine Health and OEE Integration	Decision logic for root-cause determination/analysis (diagnosis) – including data preparation steps and use of various supervised decision making and classification algorithms	Software
4	Module 2: Predictive & Dynamic Scheduling	Algorithm for Markov Decision Process and maintenance policy including spare part order schedule and maintenance schedule	Software
5	Module 2: Predictive & Dynamic Scheduling	Algorithm for maintenance opportunity window estimation with failure risk analysis	Software
6	Application Client: Module 1	Unified machine health and OEE Dashboard	Software
7	Application Client: Module 2	User interface for predictive & dynamic scheduling	Software
8	Data Files	Data Files for Testing	Software

9	Technical Report	Technical Report of the Development of Module 1 and Module 2	MS Word/PowerPoint Document
10	Instruction Manual for Module 1	Setup & Instruction Manual for Module 1	MS Word/PowerPoint Document
11	Instruction Manual for Module 2	Setup & Instruction Manual for Module 2	MS Word/PowerPoint Document
12	User's Manual for Module 1	User's Manual for Module 1	MS Word/PowerPoint Document
13	User's Manual for Module 2	User's Manual for Module 2	MS Word/PowerPoint Document
14	Teaching Modules	Teaching modules for undergraduate and graduate level courses	MS Word/PowerPoint Document
15	Final Report	Final Report to MxD	MS Word/PowerPoint Document
16	Training	Industry In-person Training and Consultancy	User Training
17	Final Presentation	Presentation at MxD and selected conference	Presentation/Demo
18	MxD Integration	Demonstration of solution at MxD location	Presentation/Demo

III. PROJECT REVIEW

USE CASES & PROBLEM STATEMENT

Many manufacturers do not have any current capabilities for predictive maintenance or dynamic scheduling. It is often the case that this lack of capabilities results in production shortfalls due to higher amounts of unplanned downtime. Although the cost of unplanned downtime various for each manufacturer, even a few hours of unplanned downtime can cost the manufacturer hundreds of thousands of dollars. It is quite clear that if unplanned downtime can be reduced, it would provide a compelling value proposition to many manufacturing organizations. Although there are individual software solutions for maintenance, production planning, and asset monitoring, there is very little to any integration of these independent software solutions. A technology that can combine MES and machine health information would provide a more holistic monitoring and decision support system for manufacturers. In addition, a dynamic scheduling tool that combines inputs from the predictive machine health and production information, could provide recommended maintenance and production schedules. This integrated solution would address the issue of costly unplanned downtime and change the maintenance paradigm from "fail and fix" to "predict and prevent."

A production manager can utilize the framework and case study developed by this project to determine the machine health as well as the production schedule, which allows us to know when machines actually need replaced to avoid unscheduled downtime (better scheduling performance) and in the long term, reduce capital expenditures.

A manufacturing engineer can utilize and integrate into this system existing off-the-shelf MES system (with OEE and dynamic scheduling modules) and a CBM system (that can compute machine health). The dynamic maintenance scheduling optimizer enables scheduling optimization dynamically and proactively by utilizing real-time machine health and production information. The flexibility of the methodology also enables companies to customize the objectives based on their own preferences, e.g. reduce inventory cost, reduce machine downtime.

Scope & Objectives

To realize the full potential of predictive analytics, OEE monitoring, and production information for more cost-efficient maintenance strategies and schedules, the team had the following objectives:

1. The customization of a predictive health monitoring system and prognostic algorithms for accurate machine health estimation and prediction.
2. A methodology for integrating production information and machine level predictive health information into an optimization model that recommends the optimal time for spare parts ordering and maintenance activities.
3. Moving towards a new paradigm for maintenance from reactive to predictive, based on the integrated system and developed scheduling tool.

Effectively, the proposed solution was aimed at monitoring the machine health, predicting failure, and finding the optimal window to perform maintenance in a proactive manner while considering the production schedule. The expected value this solution would provide would include a reduction in unplanned downtime. Additional benefits of the system could include a reduction in the shipping cost (since the part would not have to be expedited), higher machine availability, and better maintenance planning.

Technical Approach

A smart factory employs enterprise manufacturing systems that enable proactive management of the manufacturing enterprise through informed, timely, and in-depth decision making, leading to significant productivity improvements with quantifiable ROI. Creating smart and connected factories to drive productivity is the endgame for any manufacturer. Today, there are numerous commercially available software solutions that can monitor and optimize productivity and assist decision-making on the shop floor. OEE (Overall Equipment Effectiveness) is a key performance indicator output by Manufacturing Execution System (MES) software technologies and has become a recognized standard in measuring factory productivity.

Existing preventive maintenance schedules are typically manual-based and time-based, current MES helping maintenance scheduling do not consider the actual condition of the equipment and lack the predictive capability and analytics. If the spare parts for maintenance can be placed at proper times before the machine's failure time instead of being ordered after the failure occurrences, the downtime can be largely reduced.

The goal of this project is to develop an enabling technology that can bridge MES and machine health predictive solutions to provide a more holistic monitoring system and decision support system for manufacturers.

In this project, we develop a dynamic scheduler which is capable of incorporating equipment health condition and production schedule to transform the preventive maintenance or corrective maintenance to condition-based maintenance in order to optimize the predictive maintenance activities, improve the maintenance resources management and minimize machine downtime. Specifically, a scheduling threshold is introduced to provide the optimal maintenance plan with the minimum cost based on system conditions to arrange maintenance resources. For example, to arrange the spare parts for a barrel of coolant concentrate, we need to decide when to order the spare part and when to replace it in the machine. Then, there is a lead time between the time to order and the time to replace. In order to obtain the optimal plan for the particular part, we dynamically need a maintenance threshold to replace it and a scheduling threshold to order it both based on the estimated condition of that product. Furthermore, if the spare part comes too early, there is the inventory cost of planned parts; if the spare part comes too late, there is the penalty cost of the machine downtime.

The objective of this project is to minimize the overall expected cost rate in order to obtain the optimal spare part scheduling threshold and maintenance threshold based on the predicted health indexes of specific components. In this way, we can execute the corresponding optimal predictive maintenance policy once the current equipment health index hits the spare part scheduling threshold and maintenance threshold, respectively.

Fig. 1 shows the overall architecture of the developed technologies and the integration by the four parties in this collaborative effort.

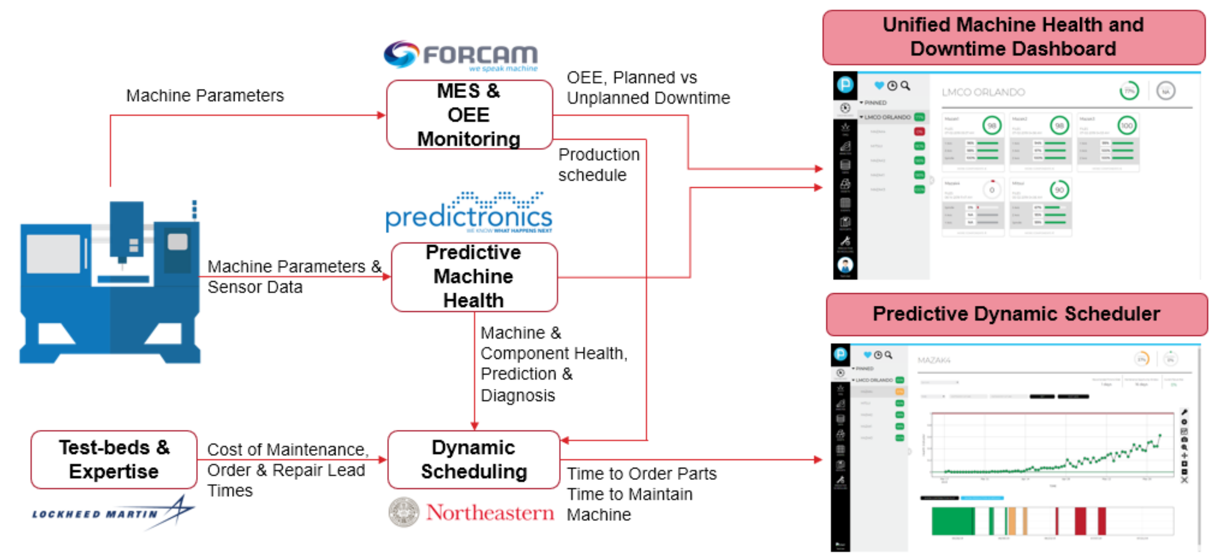

Fig. 1. The overall architecture for technology development

Project tasks:

1. <u>Sensor data collection for machine component predictive monitoring</u>

This task focuses on sensor-based data analytics for tracking machine/component degradation behavior and provide probabilistic prediction of the component future condition and remaining useful life. Statistical methods, regression methods, and machine learning have been used to build the degradation model. For each component (spindle, ball screw, coolant) relevant data was either gathered from the control system or external sensors (as needed). For the spindle and ball screw monitoring, the data was captured and triggered during a warm-up cycle of the machine. The coolant monitoring was collected on a periodic basis, such as every 6 hours. Baseline-based anomaly detection and machine learning health models were trained and deployed, effectively comparing the baseline sensor patterns to the current patterns. The health index method measures the degradation and change in the machine condition from its original baseline state. After a trend has been detected, machine learning based prediction algorithms were then used to estimate the future health state and remaining useful life of a component. This was further integrated into a dynamic scheduling algorithm, which included MES and production data as inputs into the optimization method.

1.1 Sensor-based Predictive Monitoring

The predictive monitoring solution is leveraging the Predictronics PDX software to generate health value trends (degradation curves) for key components of the machine tool. The key components would consist of the machine tool spindle, the linear axis (ball screw), as well as the coolant/fluid monitoring for this application. For a given component, various signal measurements would be collected by external sensors (e.g. vibration) or from the machine's controller. Data gathered from the machine controller would use various protocols (e.g. MTConnect) and would include measurements of the servo current for each axis, axis position, spindle load, spindle rotational speed, and spindle temperature. For the spindle health model, the key sensor signals include vibration, the spindle load, the spindle rotational speed, the spindle temperature, among others, and typically the data is collected from the same routine program that is run once per shift/day. In a similar manner, the ball screw health model is based on the servo loads from the axis, the axis position, the axis speed, among other signals.

A machine learning model learns the baseline data patterns from these measured signals and compares the current signal patterns to the baseline patterns to generate an anomaly/healthy score for each component. This health value is a scaled value in which a value of 0 is healthy and a value above 1 would indicate a severely degraded/failure condition (Fig. 2).

Fig. 2. Example health index trend over time

The spindle and ball screw health index values would be calculated over time as a new data record/pattern is captured each time the routine program is run. The health value trends are effectively one of the key elements and a pre-requisite for connecting the predictive monitoring result with the optimization algorithm. The next step is to generate predictions of the future health condition and decide on when the prediction method should be trigged.

The triggering of the prediction method is based on two aspects, the health value magnitude and the consistency in the health value trend. The health value magnitude criterion is based on a comparison of the health value to a user defined cutoff value (e.g. 0.5). In this case, a threshold that is set too high might not offer enough lead time for maintenance planning. However, a value that is set too low might result in false alarms or the prediction method being trigged when the trend is at the beginning stages and the predicted health trend is very uncertain. A correlation with time value is also calculated for the health value, to ensure that the health value is showing a consistent trend. It is not desirable to have spurious health values (outliers) trigger the prediction method, since this is not the designed use case for predictive monitoring and the maintenance scheduling algorithm. If both these criterions are satisfied, the prediction method is triggered.

The prediction method is based on the most recent health trend, which is a user defined setting, but could be 25 to 50 health values. This would represent the health trend in the last 1-3 months, which would represent the most relevant trend to consider in terms of predicting the failure and scheduling the maintenance. A second order polynomial and a robust regression method are used for fitting the current health trend. Other time-series regression models or methods could also be considered for this aspect of the predictive monitoring methodology. Based on the model fitting process and pre-defined confidence level, a prediction interval is calculated. The prediction interval is used in conjunction with random sampling to generate 1000 or more potential degradation curves. A degradation curve is an extrapolation of the health value over time, indicating a potential prediction of how the components health will degrade in the upcoming weeks (see Fig. 3).

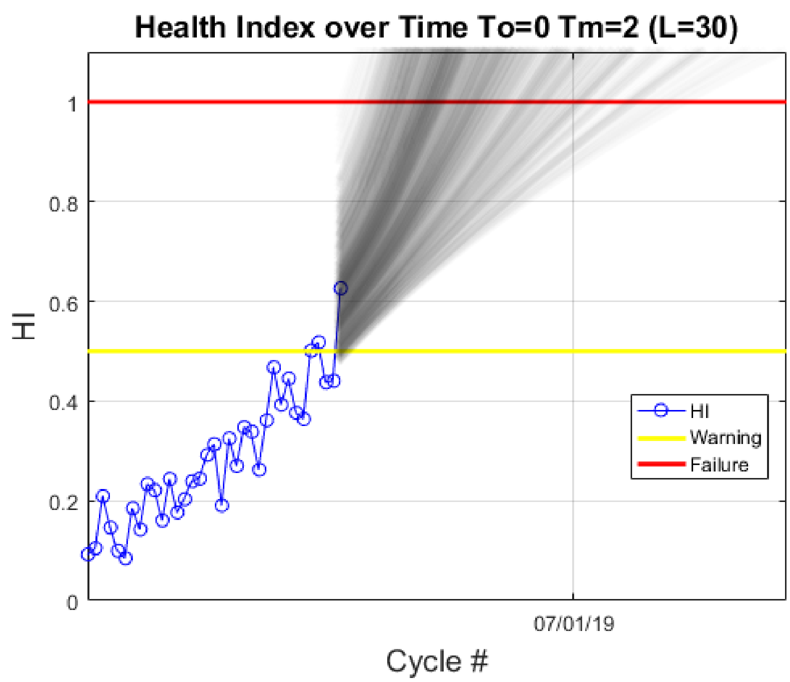

Fig. 3. Illustration of Degradation Curves

Many degradation curves are generated, since the future health trend has some uncertainty associated with this prediction, due to the sensor noise/health estimation, the future usage and loads on the machine, among other factors. The degradation curves represent the final output of the predictive monitoring solution and are one of the key inputs used by the optimization algorithm.

1.2 OEE Monitoring

Lockheed Martin has been using the FORCAM FORCE™ platform and functionality as their OEE monitoring system and integrated with their manufacturing machines and

ERP-System. To provide the needed information for the Unified Health Dashboard, this integrated solution builds the baseline for the relevant data.

FORCAM FORCE™ captures machine utilization out-of-the-box and combines it together with data from the ERP-System based on Manufacturing user input to calculate OEE.

At the beginning of the project and during first discussion of system integration between FORCAM, Predictronics and North Eastern University the data exchange functionality was discussed. The first suggestion to exchange data via access to the underlaying SQL database was withdrawn due to various concern:

- Highly system specific data structure
- Security concerns in accessing the core database

Following that discussion, the decision was made to develop and use a web-based technology in the form of open API and JSON command structure to provide relevant data to sub-system (in this case OEE metrics like Availability, Performance and Quality; and then also Production Scheduling information).

OEE Metrics are pulled on a daily basis into the Unified Health Dashboard for ease of communication. Even though the option to gather data via the open API in real time exists, this function was not developed due to system performance concerns and to avoid end user confusion potentially due to frequently changing numbers.

Throughout the project several discussions took place to evaluate the usefulness for OEE on the Unified Health Dashboard and user benefits for that metric. As item numbers can frequently change in the production shop (known as “low volume – high mix”), the metric of OEE can vary from day to day based on the schedule. This gives some end-users, especially within a maintenance department challenging data, and an easier metric like Availability was chosen to display on the Unified Dashboard. Availability is the better indicator for the Maintenance teams to identify when and how easy it will be to get access to a machine for predictive and regular maintenance activities. Together with the displayed Production Schedule they have an indicator for optimal maintenance windows within the schedule.

2. Provisioning of Production Schedule

A basic Finite Scheduling algorithm provides the basis for the Predictive Dynamic Scheduling Modell. Therefor the Finite Scheduler has all released production orders and operations for all production steps including all machines from the shop floor.

Based on the provided System Manual of FORCAM for the Detailed Scheduler, a basic queuing algorithm is used to schedule operations during the planned/scheduled time for the shop (see Fig. 4 for illustration of the scheduling).

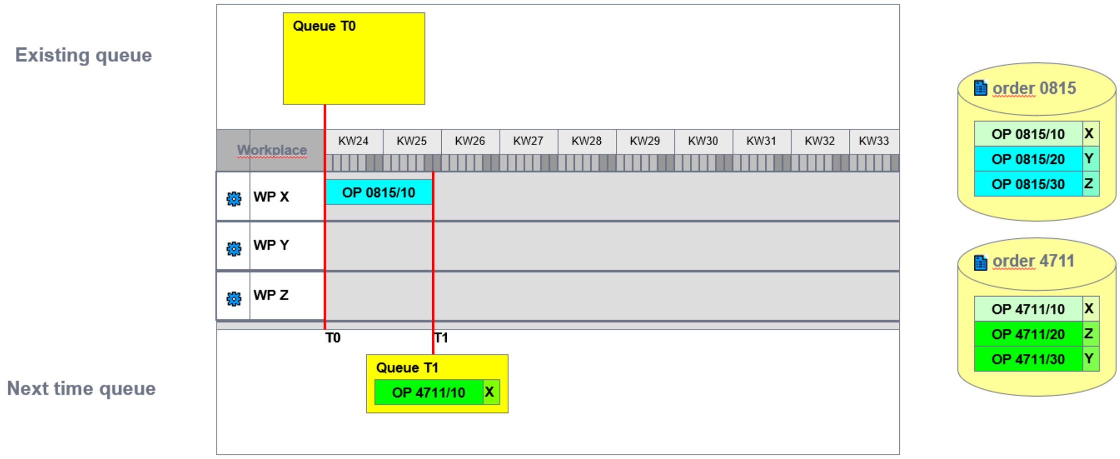

Fig. 4 Basic FORCAM FORCE detailed scheduling methodology

This queuing algorithm allows the system to optimize the sequence of operations e.g. based on already confirmed production quantities to continue on other machines/workplaces.

It provides a more realistic schedule as it also takes realistic machine capacity in consideration.

Figure 5 below compares an ERP-system based planning without queues and capacity information with the results from the Detailed Scheduler.

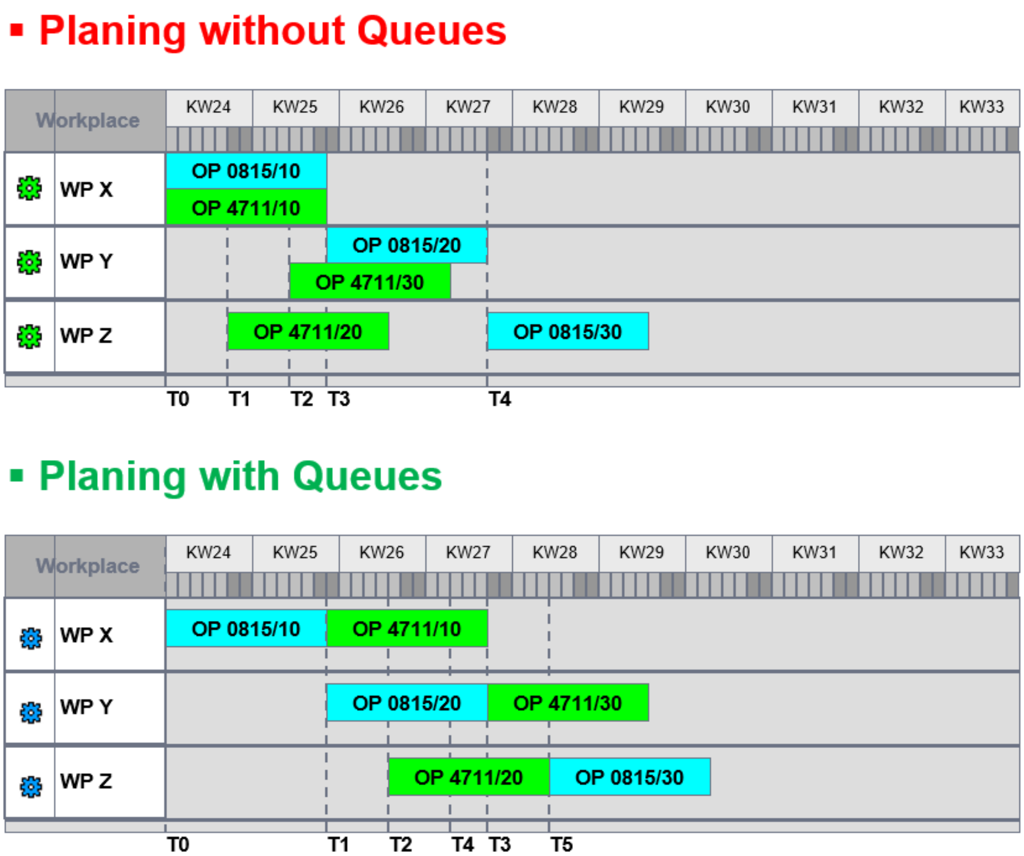

Fig. 5 Basic FORCAM FORCE™ Detailed Scheduling Result

The result of the finite scheduler is accessible via an open API / JSON interface and specific call for operations scheduled on the defined machines in scope of this project.

The used API (`/api/v1/operations/{operationId}/scheduledDates) provides the following information:`

- Earliest Start & End Dates
- Latest Start & End Dates
- Scheduled Start & End Dates

Based on the machines defined for the scope of this project, the API needed to be utilized in a two-step process:

i. The API needs to provide all operations scheduled for the machine.
ii. in a second step, the system needs to get the scheduling information for each operation individually.

During the integration phase of the project, various discussions about the frequency of provisioning the scheduled information lead to the conclusion to gather the information on a daily routine during the night. The team was concerned about the amount of potential ten-thousands of operations being calculated and scheduled frequently; impacting system performance, usability and end-user experience.

3. <u>Dynamic scheduler development through optimization modelling and predictive monitoring information and production schedule</u>

In this task, the team focused on a holistic optimization model and algorithm development that integrate the predictive monitoring information (probabilistic prediction of future states) and the production information as inputs and constraints. Parameters of the model include spare part lead time, cost related to downtime, maintenance, and spare part shipping. Three optimization algorithms have been developed to solve for the optimal decisions (1) exhaustive search in discrete state space, (2) Genetic Algorithm (GA), and (3) Simulated Annealing. Results of the three algorithms have been compared and sensitivity analysis regarding parameter variability has been conducted.

Challenges & insights: The first version of the model considers the predictive machine health information only to provide an ideal or theoretical optimal decision of “when to order spare parts” and “when to start predictive maintenance”. Improvements have been made when production information (e.g., future production schedule) is integrated to provide a more practical recommendation on “maintenance opportunity windows” with the associated risk of failure.

The overall methodology of the dynamic scheduling optimizer is illustrated in Fig. 6. Inputs collected from all three sources with heterogeneous data type are fed into an optimization model. The optimization model is set for determining the optimal thresholds for triggering two actions: (1) time to order spare parts, and (2) time to start predictive maintenance, such that the overall cost rate over the machine/component degradation cycle is minimized. The cost components include downtime cost, maintenance cost, and spare part inventory cost computed based upon the probabilistic prediction of the degradation trend given by the predictive monitoring function.

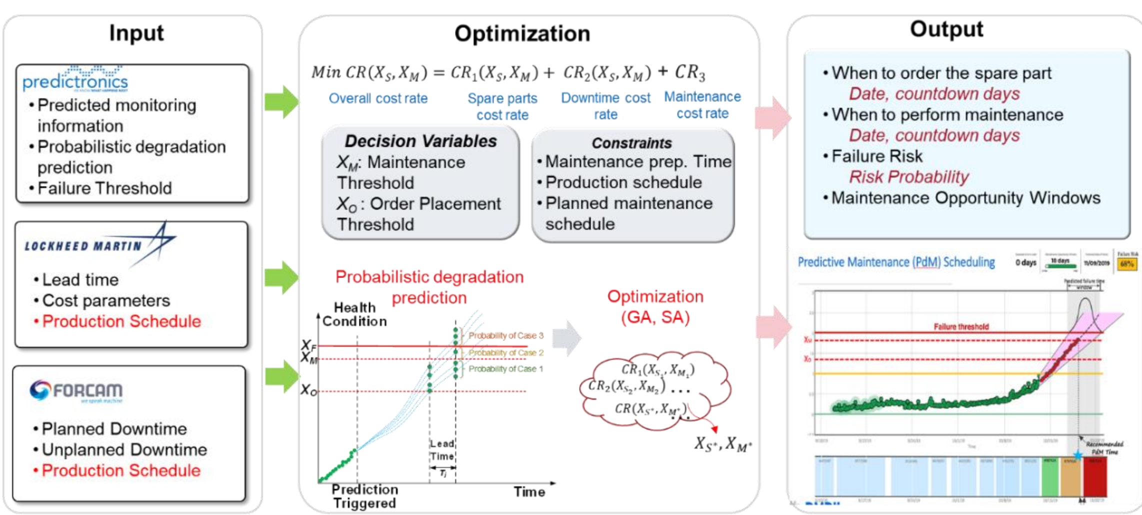

Fig. 6 The overall methodology framework of the dynamic scheduling optimizer composed of an input module, core optimization modeling module, and the output module for predictive maintenance alerts and maintenance opportunity identification.

*Details of the optimization algorithms are provided in the Technical Report.

The PM scheduling intelligence has been improved from several key performance perspectives: (1) unplanned downtime reduction, (2) machine availability improvement (OEE improvement), (3) spare part readiness improvement, and (4) cost saving by avoiding expedited shipping.

4. Unified dashboard development for predictive monitoring based dynamic scheduling for predictive maintenance

This task focuses on developing a unified dashboard that consists of two modules: (I) machine predictive monitoring, and (II) dynamic PM scheduling. It aims to provide MES solutions with a drill-down information capability by providing the health condition of machine and its components from a machine health monitoring system; Most importantly, rules and logic have been developed so that the interaction of metrics and associated parameters between the monitoring function (machine health) and the dynamic PM scheduling function become more intuitive to the end users.

In the final testing of the unified Machine Health and Dynamic Scheduling intuitive dashboard, four machines are connected for monitoring and one simulated "virtual" machine is built for testing and validating all the designed functions. One of the main challenges is that component degradation takes many months to develop and observe. Given the project time period, components with failure modes that exhibit faster degradation rate might be one aspect that could have been considered. Alternatively, additional time and data needed for validating the predictive health models and scheduling algorithm could have also been considered.

The unified dashboard for predictive monitoring and maintenance scheduling is shown in Fig. 7. At the bottom of the Asset View is the production schedule, with the associated risk. The production schedule starts from the date of the last recorded health value in the health plot (only future orders are shown). Each block in the production schedule has a scheduled start and end date, operation number, PO number, and risk. The risk represents the % risk that the component fails before the order's end date, if the risk is high the color of the order will be red. To see all the order information, one can hover over the order block in the schedule.

The information in the top right includes the Recommended Time to Order spare parts and the Maintenance Opportunity Window provided by the Predictive Scheduler, which is based on the Predictive Scheduling settings, and the most recent health trend for the selected component. Initially these values will be "NA", when there is a trend in the health, and the health reaches a certain level, the Predictive Scheduler will be triggered (see the Project Settings section for more information on the trigger criteria). Also shown in the top right is the Current Failure Risk, which is the risk that the component fails during the current order.

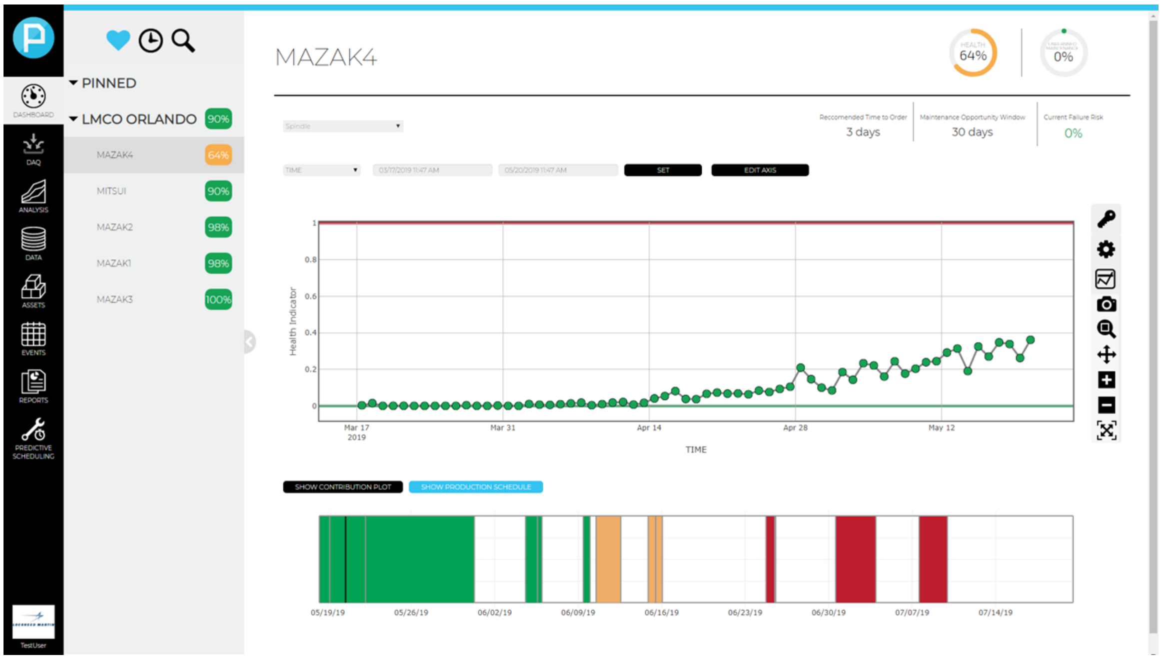

Fig. 7 A screenshot of the unified dashboard with predictive health monitoring and maintenance scheduling decision support.

Planned Benefits

The value of the proposed technology is changing today's factory operations from a reactive environment centered around preventive maintenance to an agile, just-in-time maintenance environment. The combined power of combining real-time OEE metrics delivered by MES together with in-depth machine health analytics will immediately impact and can significantly improve the availability metric of OEE by reducing unplanned downtime. This will ultimately reduce spare inventory levels and avoid expedited shipping cost.

At the end of this project, users can benefit from the following aspects:

- Customize the predictive health monitoring system and prognostics algorithms for accurate machine health estimation and prediction;
- Synthesize system-level factory information and machine-level predictive health information into an optimization tool for maintenance planning;
- Achieve predictive and dynamic scheduling of maintenance activities considering production schedules and spare part inventory and shipping.

IV. KPI'S & METRICS

The validation section provides the results of the comparison of success metrics and KPI and their improvement after deploying the dynamic predictive maintenance schedule compared with the current reactive maintenance. Predictive maintenance and predictive maintenance (PM) opportunity windows are compared with the reactive maintenance in terms of machine downtime, availability and cost (average cost per day). The length of time for validation begins with the time point when prediction is triggered and ends when a failure occurs, or maintenance is performed (a full degradation cycle).

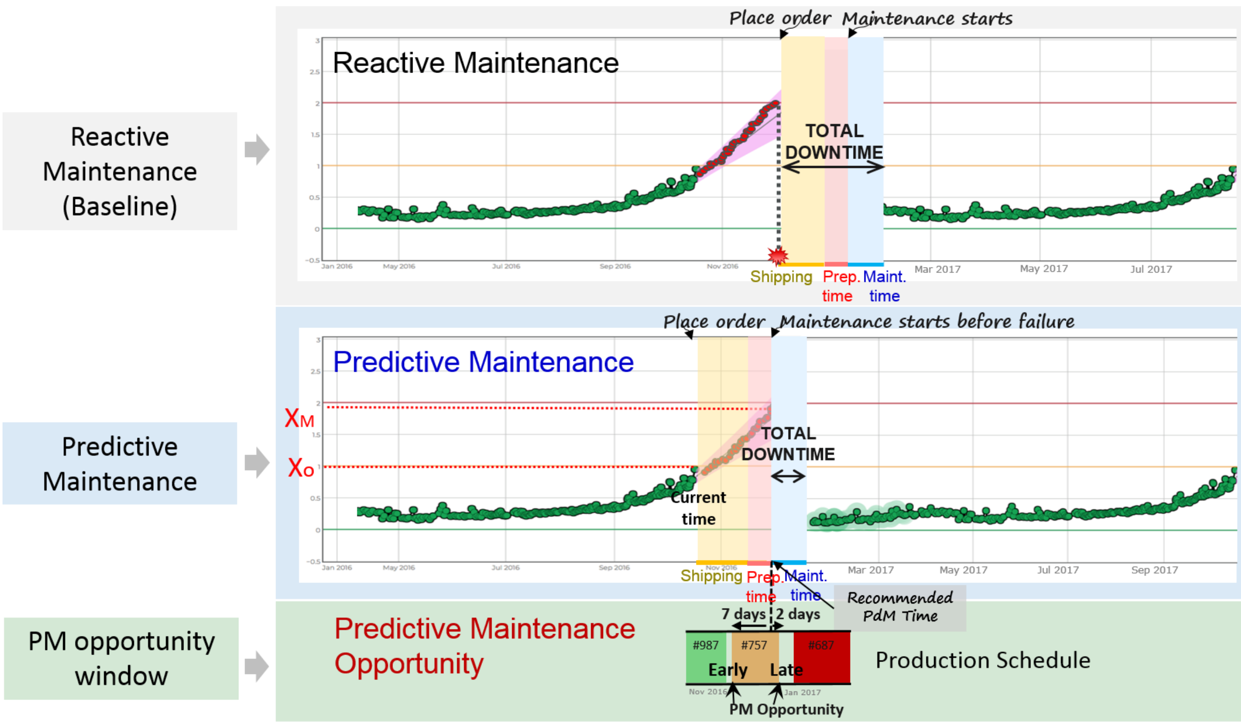

Fig. 8. Three maintenance strategies are presented. Reactive maintenance employed as the existing maintenance policy indicates a spare part is ordered whenever component failure is detected. Predictive maintenance indicates that spare part is ordered while machine is still functioning, and maintenance is performed whenever the maintenance time T_m is reached. PM opportunity window indicates that taking advantage of machine's nonoperation time either incurs maintenance early at the beginning of the order or postpones maintenance late at the end of the order. The optimal T_m is within a created dummy order with length 9 days, maintenance can be performed 7 days earlier (early maintenance) and postponed 2 days later (late maintenance). Machine downtime consists of the spare part lead time (shipping time), maintenance preparation time and maintenance performance time.

Table 1. Improvement by predictive maintenance

Lead Time (d)	Reactive Maintenance			Predictive Maintenance			Downtime Reduction	Availability Improvement
	Downtime	Availability	Average Cost	Down time	Availability	Average Cost		
1	2	96.15%	875	2	96.15%	875	0%	0.00%
2	3	94.34%	1047	3	94.34%	1047	0%	0.00%
3	4	92.59%	1213	1	98.04%	696	75.00%	5.89%
4	5	90.91%	1373	1	98.04%	696	80.00%	7.84%
5	6	89.29%	1527	1	98.04%	696	83.33%	9.80%
6	7	87.72%	1675	1	98.04%	696	85.71%	11.76%
7	8	86.21%	1819	1	98.04%	696	87.50%	13.72%
8	9	84.75%	1958	1	98.04%	696	88.89%	15.68%
9	10	83.33%	2092	1	98.04%	696	90.00%	17.65%
10	11	81.97%	2221	1	98.04%	696	90.91%	19.60%
11	12	80.65%	2347	1	98.04%	696	91.67%	21.56%
12	13	79.37%	2468	1	98.04%	696	92.31%	23.52%
13	14	78.13%	2586	1	98.04%	696	92.86%	25.48%
14	15	76.92%	2700	1	98.04%	696	93.33%	27.46%
15	16	75.76%	2811	1	98.04%	696	93.75%	29.41%

Summary:

The results demonstrate the efficiency of predictive maintenance and predictive maintenance opportunity window, through the predictive monitoring and dynamic maintenance scheduling techniques. Significant improvements can be observed from three key metrics including machine downtime reduction, availability improvement and manufacturing cost reduction after implementing the dynamic maintenance scheduler. Additional insights are revealed by comparing PM during opportunity windows with the theoretical optimal PM schedule. An opportunity window with early maintenance and performing maintenance ahead of time can mitigate the risk of machine failure, avoid machine breakdown, and may underutilize the component. On the contrary, late maintenance and putting off maintenance, may increase the risk of machine failure and could result in unnecessary machine downtime.

Component Failure Use Case:

Near the end of the project one of the spindle components failed on September 30th. The system wasn't deployed for the spindle at that time, since it did not have enough data for a baseline (14 days of data is required for a baseline). However, early signs of failure can be seen in the data that was collected prior to the failure, leading to believe spindle degradation would have been detected a couple weeks prior to the failure.

Shown in Fig. 9, the vibration at the shafts rotational frequency was much higher a couple days before the failure on September 25th.

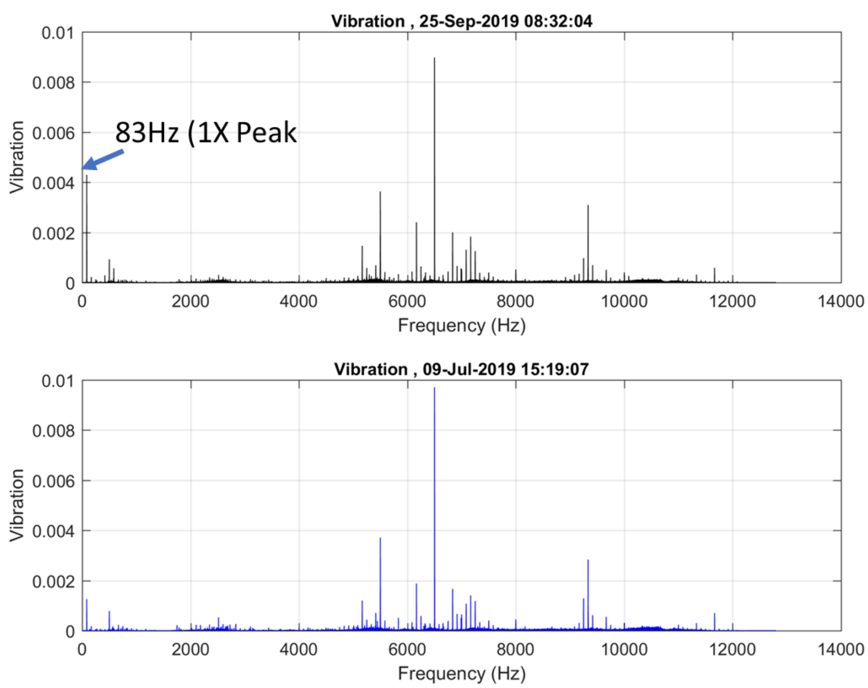

Fig. 9. Vibration frequency spectrum a couple days before the spindle failure, and a couple months before the spindle failure.

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Fig. 10 shows this shaft frequency feature for all the data files leading up to the spindle failure on 9/30/2019. There are only 14 data files recorded before the failure, but it can be argued that there was a significant increase on September 4th where the feature increased by about 6 times what it initially was (went from ~0.002 to ~0.012). Since this feature was used as an input in the spindle models, it's believed if there was enough baseline data for the health model the spindle health index would have been high by September 4th. For this machine spare spindles were in stock, which means a couple weeks early notice would have been enough time to replace the spindle before the failure occurred.

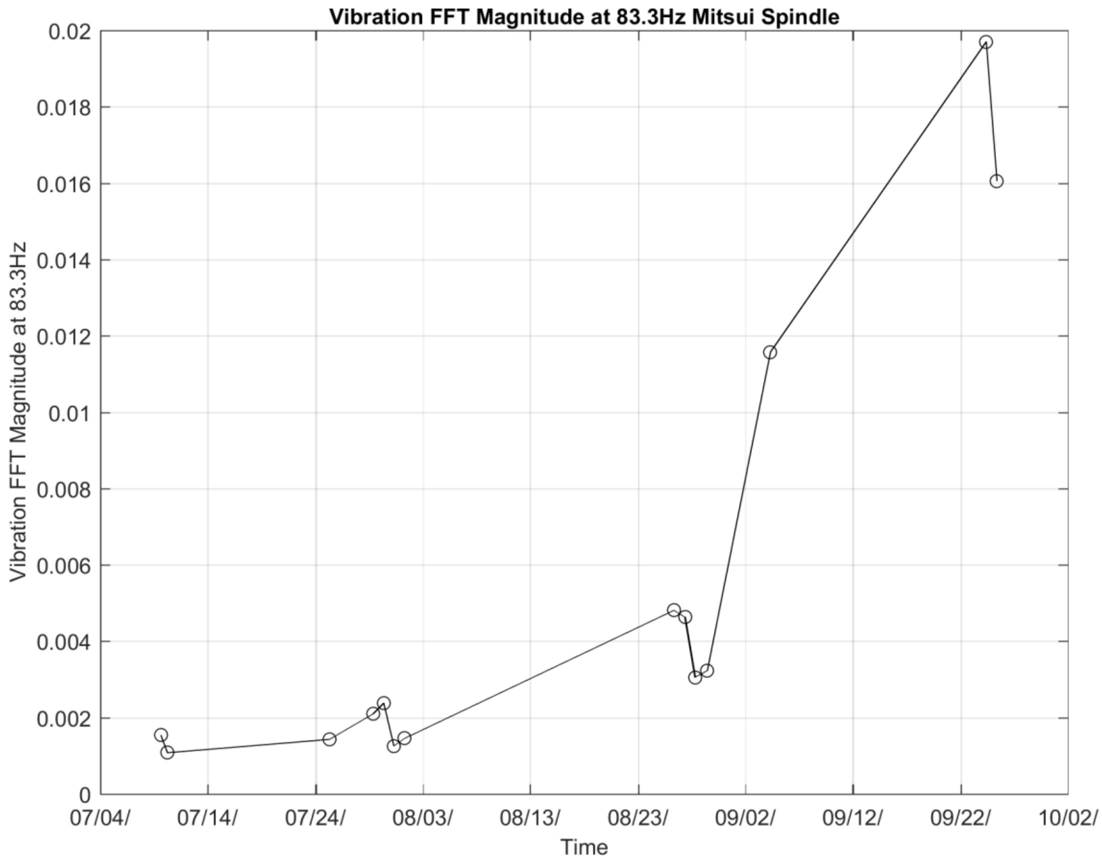

Fig. 10. Shaft frequency feature for all the 14 data files leading up to the spindle failure on 9/30/2019

V. TECHNOLOGY OUTCOMES

Technology Deliverables

#	Deliverable Name	Description	Format of Delivery
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7	Application Client: Module 2	User interface for predictive & dynamic scheduling	Software
8	Data Files	Data Files for Testing	Software

Please reference the full MxD 16-04-01 Technical Report for detailed descriptions of these deliverables as well as additional architecture, analysis, and background information (note, limited to tiers 1 and 2 members only).

System Overview

The key deliverable of the project is a dynamic scheduling tool that combines inputs from a machine health monitoring system and production information system, to provide recommendation on maintenance and production schedules. It consists of two major parts: a unified dashboard that combines machine health and unplanned downtime; and a dynamic scheduler that objectively computes for a maintenance opportunity window given an asset's future production schedule. The unified dashboard enables the user to correlate whether an increase in unplanned downtime is associated with machine health degradation. Meanwhile, the dynamic scheduling would provide more granularity with regard to the predicted failure time and the best opportunities for performing maintenance. The dynamic scheduler is triggered whenever a certain level of sustained degradation is observed from a monitored asset's component. The scheduling tool will then compute for optimum time window when to order a part replacement, when to do maintenance, as well as the risk of not completing a task for future production orders.

The scheduling tool has 3 major sources of information: machine health (from a predictive health monitoring system), unplanned downtime and production order schedule (from an OEE system), and schedule cost optimization parameters (from the end-user).

System Requirements

The system requirements for each technology (i.e., FORCAM, Predictronics, and Northeastern University) are outlined below:

FORCAM:

System Architecture Overview
2-Tier Architecture (up to 100 workplaces): ● 1 Database Server (see specs below) ● 1 Application Server (see specs below) with embedded data acquisition server
3-Tier Architecture (for more than 100 workplaces): ● 1 Database Server (see specs below) ● 1 Application Server (see specs below) ● 1+ Data Acquisition Server(s) (up to 100 workplaces per server)

Minimum Technical Requirements
Database Server: ● 1 Server (physical or virtual environment) dedicated only for use with FORCAM FORCE™ ● CPU with at least Haswell technology (e.g. Intel Xeon E5) or higher, 4 Cores, clocked with > 2 GHz ● 16 GB RAM

- Operating system: Windows Server or Unix, Linux
- Antivirus software: The recommendations of the OS vendor must be strictly adhered to. For Microsoft Tech Net Anti-Virus Exclusion List or the latest version
- SQL Server 2014, SQL Server 2016, SQL Server 2017 or Oracle 12c
- HDD Raid Level 1, no striping for physical devices
- Best practice: 3 physically separated disks with
    - 100 GB + 1 GB per workplace for data
    - 100 GB for log space
    - 100 GB for tempdb and backups

Application Server:

- 1 Server (physical or virtualized environment) dedicated only for use with FORCAM FORCE™ (without preceding load balancer)
- CPU with at least Haswell technology (e.g. Intel Xeon E5) or higher, clocked with > 2 GHz
    - 4 Cores for up to 150 Workplaces
    - + 2 Cores per additional 100 workplaces
- 22 GB RAM + 50 MB per workplace for a basic setup
    - + 2 GB for every additional module (fftracing, ffdnc, ffscheduler, ffwebservices, etc.)
    - Basic setup includes: ffruntime ignite, ffruntime, ffworkbench, ffworker, ffnewoffice (Modeller+Visualisation), ffnewoffice background, DCU/DACQ
- Operating system: Windows Server 2012 (R2) or Windows Server 2016
- Microsoft .NET Framework Version 3.5 must be installed
- Antivirus software:
    - The recommendations of the OS vendor must be strictly adhered to. For Microsoft Tech Net Anti-Virus Exclusion List (or the latest version).
    - The Folder for the FORCAM FORCE™ applications should be excluded from the antivirus scan, as this may drastically impede performance.
- For information regarding required ports, please refer to the “FORCAM Force™ Firewall Requirements”
- HDD RAID system (for physical devices), best practice: RAID Level 1
    - 1 partition physically separated from the OS containing 250 GB exclusive use for FORCAM FORCE™
- Java 8 (JDK and JRE), 64-bit, Version 201. If 2 tier architecture is being used, install 32-bit JDK also.
- Newest available version of supported browser with HTML5 capability (Firefox, Chrome, or Edge)
- Install Open Office if export of pdf files is needed

Data Acquisition Server (for 3-Tier Architecture):

- 1 Server (physical or virtual environment) dedicated only for use with FORCAM FORCE™
- CPU with at least Haswell technology (e.g. Intel Xeon E5) or higher, 4 Cores, clocked with > 2 GHz
- 12 GB RAM + 0.5 GB RAM per additional DCU
- At least 100 GB of available disk space
- Operating system: Windows Server 2012 (R2) or Windows Server 2016
- Antivirus software:

- The recommendations of the OS vendor must be strictly adhered to. For Microsoft Tech Net Anti-Virus Exclusion List (or the latest version).
- The Folder for the FORCAM FORCE™ applications should be excluded from the antivirus scan, as this may impede the performance drastically

- For information regarding required ports, please refer to the "FORCAM Force™ Firewall Requirements"
- Only required for 3 tier architecture
- Java 8 (JDK), 32 and 64 Bit, Version 201

Network:

- 2x 1 Gbit NIC1 per server in failsafe --/load balancing mode
- Database-, application-, and data acquisition servers connected to switched LAN (1 Gbit or better)
- Shop floor network connected with at least 100 Mbit uplink to office network. Best practice: Use LAN instead of WLAN to avoid problems with electro-magnetic interferences)
- For use in dedicated environments: Optical (fiber) connections to reduce latency

Predictronics:

Minimum Technical Requirements

PDX Deploy Server:

- 1 Server (physical or virtual environment) dedicated only for use with PDX Deploy
- CPU: Intel i5/i7 3.0GHz or better (or AMD equivalent), 4 cores;
- RAM: 16 GB or higher
- Operating system: Windows Server 2016 or higher, 64-bit Ubuntu Server 16.04 LTS or Red hat v7.3
- HDD: 500 GB or higher (dependent on how much data will be processed)
- Antivirus software: The recommendations of the OS vendor must be strictly adhered to.
- Other Package/Software: MATLAB Runtime v9.1 (R2016b), Docker v1.12.6(only for Linux Server), MongoDB v3.4.4, RestartOnCrash (latest released version-only for windows server)
- Server must be assigned with fixed IP Address
- The server must have full internet access for installation.
- The installation user must have root/admin access to the system.
- Firewall requirements: Inbound ports 443 and outbound ports 80,443, 465, 587 must be open

Data for Predictive Monitoring & Dynamic Scheduler:

MASTER DATA:
- Asset ID
- Lead Time to Order - Per Component [in days]
- Component Cost [$]
- Delivery/Expedited Service Cost [$]
- Downtime cost (production loss per unit time),
- Spare part shipping and inventory information (lead time, cost),
- Maintenance cost (optional),

DAILY DATA:

a) From OEE System/Production Scheduling System:
- Asset ID
- TimeStamp
- Downtime [hours]
- Scheduled Operating Time [hours]
- Asset ID
- Production Order ID
- Operation ID
- Planned Start Time
- Planned End Time

b) From Machine Health Monitoring System:
- Asset ID
- Component ID
- Component Health Index
- Component Health Threshold
- TimeStamp

Data for Dynamic Scheduler:

Downtime cost (production loss per unit time), spare part shipping and inventory information (lead time, cost), maintenance cost (optional), production schedule

SYSTEM ARCHITECTURE

The following diagram provides the full architecture of the project including the technology components provided by Predictronics, Northeastern University, and FORCAM. The architecture for the individual components is outlined in the subsequent sections.

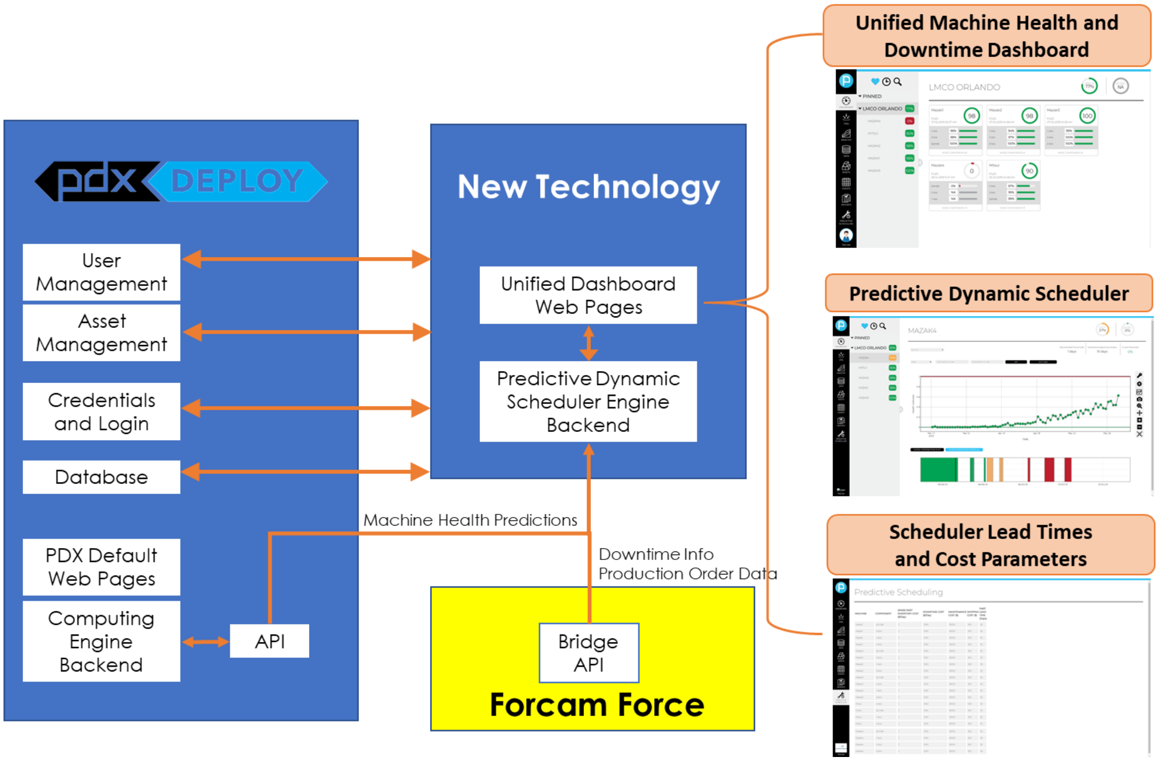

Fig. 11. Overall project application architecture

Cyber Security Requirements:

The system architecture described in this report aligns with traditional cyber security protocols and those in place during the course of this project (i.e., firewall rule settings, etc.). The machine-related data captured in this solution is considered business critical and, therefore, resides within a separate, isolated network environment. This data is only accessible for selected end users who have access to this restricted environment.

FORCAM:

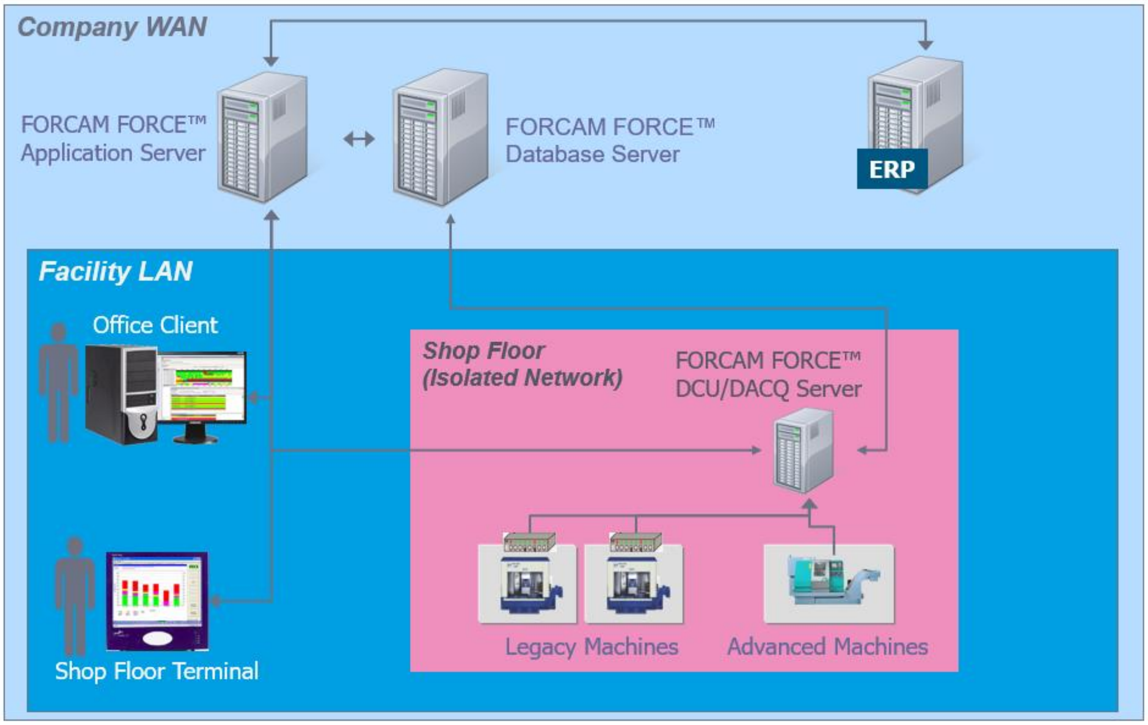

Fig. 12. FORCAM FORCE™ system architecture

Predictronics:

The solution developed in this project is currently exists as a plugin to PDX Deploy. Due to time constraints and scope, the project tasks are limited to developing the new modules and functionalities that do not replicate the existing technologies (FORCAM and Predictronics' PDX). The new technology has two main aspects: the web pages and the back-end computing module. The web pages consist of the unified dashboard (that shows both unplanned downtime and machine health in a single accessible web page), the machine health view that incorporates the production order data (this allows the user to identify maintenance opportunity windows when maintenance activities can be planned to happen, before the failure, but in between scheduled production runs), and a web form that allows the user to input scheduling lead times to order parts and costs associated with part order. Data from PDX and FORCAM are received using their respective APIs.

The other aspects of the application, including, but not limited to, user and asset management, login and credentials, database, asset hierarchy, currently leverage PDX existing functionality. Should other machine health and OEE systems be utilized, integration tasks have to be performed so as to use either the machine health or OEE system's existing fundamental modules.

Features & Attributes

The face of the project solution is viewed through the Predictronics application. The features of this technology are extended with the data collection and dynamic scheduling information collected by the FORCAM FORCE platform and the predictive scheduling functionality incorporated by Northeastern University. The union of these technologies provides the customer with a robust set of real-time data and predictive monitoring and scheduling information. The core features are outlined below:

- Machine health index (%) with predictive maintenance
- Machine degradation tracking (on target, ahead/behind expectation)
- Time to order (spare parts)
- Time to repair (scheduled maintenance planning)

Key Performance Indicators:

- Unplanned Downtime (% reduction)
- Availability (% improvement)
- Spare parts shipping and inventory cost ($)

Core Benefits:

- Reduction in unplanned downtime
- Improvement in equipment availability and utilization
- Saving in shipping cost of spare parts (avoid expedited shipping)
- Relaxing the lead time and preparation time for maintenance activities

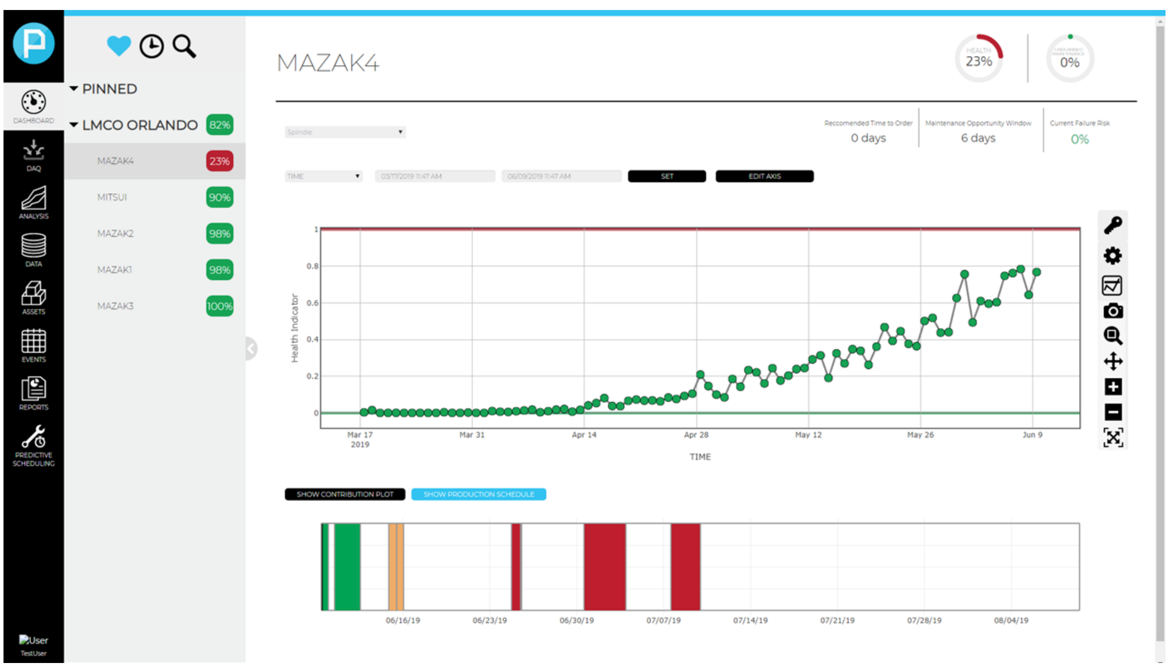

Fig. 13. Predictronics PDX DAQ Dashboard

TARGET USERS & MODES OF OPERATION

The target users, or those users who would benefit the most by using the tool and/or incorporating this tool into the organization's manufacturing or related business processes would be:

- Maintenance engineers
  Use case: As a maintenance engineer, I want to get early insights on the health of critical machine components and then receive guidance on the optimal time to schedule the maintenance activities.
- Automation engineers
  Use case: As an automation engineer, I want to monitor machine availability and control data in concert with production schedules to understand how control signals are converted to machine operating states, and how those states translate into asset productivity.
- Research engineers
  Use case: As a research engineer, I want to analyze the degradation of machine assets with data from multiple sensors to better understand how we can improve machine uptime and reduce operating costs.
- Production and operations management
  Use case: As a production manager, I can utilize this tool to determine the machine health as well as optimize the maintenance schedule.
- Scheduling personnel
  Use case: As a scheduling associate, I want to match my machinery assets with my production schedules to determine the optimal mix for production efficiency and overall throughput.

These users should have proficiency with MES, MRP, scheduling, forecasting, predictive analytics and related software. Additionally, the user should be able to interpret the data and apply it to ongoing manufacturing processes.

Use case: "As a maintenance engineer, I want to get early insights on the health of critical machine components and then receive guidance on the optimal time to schedule the maintenance activities."

SOFTWARE DEVELOPMENT/DESIGN DOCUMENTATION

The content developed during this project include a combination of software (Predictronics and Matlab formats), data files, setup and instructions manuals, user manuals, teaching modules, and technical reports. The software developed herein is built upon the existing FORCAM and Predictronics software platforms.

The FORCAM FORCE™ and Predictronics DAQ and Deploy applications must be licensed from FORCAM and Predictronics respectively. All other project-developed content can be accessed via the MxD Membership Portal in accordance with your organization's membership tier.

VI. INDUSTRY IMPACT

The potential industry impact of this combined solution is: (1) improved manufacturing productivity via higher asset utilization, (2) optimized supply chain channels through reduced production inventory, and (3) overall reduction in manufacturing costs. Lockheed Martin is piloting this solution with subsequent expansion expected. As the deployment evolves beyond the pilot, we anticipate realizing these impacts.

This solution is beneficial to discrete manufacturers seeking to optimize their production capabilities by implementing real-time machine monitoring with integrating predictive analytics to schedule maintenance windows. Additionally, universities with research and curriculum built around similar applications would also benefit from utilizing the solution outlined in this project.

VII. TRANSITION PLAN

Transition Summary

This solution contains both commercial (industrial) and educational (university) components designed for use across multiple implementation types. The primary users of this solution will be small-, medium-, and large-scale discrete manufacturers with moderate to high asset utilization, and educational institutions with pedagogy developed around these commercial applications.

As of the writing of this report, this solution is being piloted by the project's commercial partner, Lockheed Martin, with a small sampling of disparate machinery within their manufacturing facility. Specific transducers have been added to these pilot machines, including vibration and fluid coolant sensors, to monitor machine degradation over time and transmit this data to the project software suite. As this project evolves from pilot to full implementation over the coming months, we anticipate the following next steps:

- Running the deployed system for several months, fine-tuning the algorithmic models, and obtaining additional feedback from Lockheed Martin
- Extending the solution to other machines at the existing Lockheed Martin facility and to other Lockheed Martin facilities with similar manufacturing environments and use cases
- Evaluating this technology with other MxD member companies

The deliverables of this project, including software, data files, installation and user manuals, and technical reports will be available on the MxD portal for use by Tier 1 & 2 members.

NEXT STEPS & CHALLENGES

The project has undergone system integration and piloting of the solution at the Lockheed Martin location. Preliminary testing was completed successfully. However, the nature of the solution requires weeks or months to fully test and develop. Consequently, only piloting of this solution has been completed at the time of submission.

Please reference the Setup (Installation and Use) folder in the MxD Final Deliverables folder for detailed instructions outlining the full installation requirements for the technologies provided by each participant as well as any system integration requirements and configurations.

- Tier 1 and Tier 2 MXD members have access to the developed tool and other project deliverables free of charge
- The customer should have a health monitoring system in place, an OEE monitoring system and a factory information system
- If the same machine health and OEE monitoring system is used, support will be provided
- Documentation is provided and services can be considered if other systems are used

Note that the software application tools utilized by the project partners may not be required for future deployments. For example, other machine data collection platforms other than FORCAM, and other predictive analytics platforms other than Predictronics are applicable. However, additional integration and software development work will be required if pursuing this solution without the project partner technologies intact.

VIII. WORKFORCE DEVELOPMENT

#	Deliverable Name	Description and Learning Outcomes	Target Audience
14	Teaching Modules	Description: Teaching modules for undergraduate and graduate level courses Outcome: University-level instructor can guide students in the setup, configuration, and general use of Modules 1 and 2	Undergraduate and graduate students
16	Training	Description: Industry In-person Training and Consultancy Outcome: Industry key users can fully use Modules 1 and 2	Industry students

Target audience and learning outcomes

Teaching Modules in Manufacturing Courses at Northeastern University (IE 4530 Manufacturing Systems and Techniques:

- Undergraduate/Graduate Students
  - Key Learning #1: *Methods and techniques for manufacturing equipment and component condition monitoring*
  - Key Learning #2: *Data analytics to estimate and predict time-series data from sensors*
  - Key Learning #3: *Optimization methods for maintenance scheduling in a dynamic manner*
  - Key Learning #4: *Evaluation methods for equipment and machine performance (i.e., OEE)*
- Community College Students in Manufacturing Science and Engineering
  - Key Learning #1: *Data analytics for production system monitoring*
  - Key Learning #2: *Optimization modeling methods for maintenance scheduling and planning*

Deliverable #2 Industry Training and Consultancy (including activities to MxD members):

- Manufacturing companies with needs of preventive and predictive maintenance strategy

- Key Learning #1: *Techniques of general data collection, data analytics, algorithms, and optimization.*
- Key Learning #2: *Mindset shift from "fail and fix" to "predict and prevent"*
- Key Learning #3: *Preparation for existing manufacturing workforce to adapt to AI and data analytics-enabled smart manufacturing technologies*
- Key Learning #4: *Establish the mindset to appreciate and gain interest in emerging data-driven predictive analytics and sensor-informed preventive & predictive maintenance & operations*

IX. CONCLUSIONS & RECOMMENDATIONS

The proposed solution developed and the objective measures realized through the piloting of this project at Lockheed Martin demonstrated the specific need for predictive measuring of machine degradation into a quantifiable health index score that can be used to (1) dynamically schedule production orders without risk of machine downtime, and (2) proactively schedule maintenance windows and reduce non-value-added downtime. Ultimately, the following benefits may be realized by future users:

- Customized the predictive health monitoring system and prognostics algorithms for accurate machine health estimation and prediction;
- Synthesized system-level factory information and machine-level predictive health information into an optimization tool for maintenance planning;
- Achieved predictive and dynamic scheduling of maintenance activities considering production schedules and spare part inventory and shipping.

The project has undergone system integration and piloting of the solution at the Lockheed Martin location. Preliminary testing was completed successfully. However, the nature of the solution requires weeks or months to fully test and develop. Consequently, only piloting of this solution has been completed at the time of submission.

Replication of this solution is outlined in two parts: (1) the system installation and configuration documentation as included in the core deliverables package, and (2) the project technical report. Existing configurations, mappings, and sample data are provided for re-implementation into future user environments.

The integration of these disparate technologies (i.e., FORCAM, Predictronics, and Northeastern University) can be co-opted for use by other similar technologies already in place by future users. In other words, another MES system other than FORCAM can be used for machine data collection. Likewise, another predictive analytics package other than Predictronics can be used to calculate machine health over time. However, this solution was developed around the specific capabilities and functions of these technologies. The ability to implement this solution using a hybrid of these technologies may not be directly transferrable and could be time consuming and costly.

The best practices for rolling out a similar solution are outlined below:

1. Pilot the solution at a site with suitable discrete manufacturing operations, with machinery suitable for data collection, and with production scheduling information available via ERP or similar. For this project, the FORCAM system pulls production schedule information directly from the Lockheed Martin SAP system.
2. Identify specific machines for piloting that have manufacturing usage representative of the larger facility. For this project, six machines were selected that included Mazak and Mitsui.

Potential follow-on research includes the following several possible directions:

a) **Integration machine usage information into the predictive monitoring and make the prediction model usage or operational-condition adaptive.** The operating condition such as feed rate, depth of cut, spindle speed could affect the component degradation rate. By taking all these factors into a degradation model can be challenging due to the expensive data collection process but it will improve the prediction accuracy.

b) **Consideration of the impact of future/planned production schedule in the dynamic scheduling optimizer** --- enabling adaptive scheduling according to the production schedule. This would require frequent model update and accurate machine health prediction model.

c) **Correlating product quality with machine health state** -- this would help better understand the co-effect between machine degradation (e.g., tool wear, lubricant condition) and parts quality (surface integrity, etc.)

X. LESSONS LEARNED

The team has achieved the project goals of achieving an integrated solution for predictive monitoring and dynamic maintenance scheduling. The methodology and integrated software functions have been verified and validated on a digital machine which automatically queries data from the monitoring system and production scheduling system. A full pilot system is going to happen in the production environment (4 testbed machines) when their degradation trends start to develop and trigger the full function of the dynamic scheduler. Evaluation of the technology and solution might happen during the post-project support.

Technical lesson learned:

- Under-estimation of sensor installation, data collection, IT preparation, and cyber security steps.
    - More time should be allocated for these steps and some of these steps could be started prior to the actual project start.

- The IT preparation and cyber security steps for this implementation would be considered more comprehensive than many manufacturers – other implementations would be faster with regards to these elements.
- Integration of multiple systems across various security barriers can add value but it is challenging to integrate these systems.
    - Further benchmarking on the integration of various manufacturing software's should be considered, including the effort needed to perform the integration, whether standards would help, and what have been the documented lessons learned on this topic.
- Component degradation might take many months to observe.
    - Spindle failure is a high value use case, but one might not observe a failure in the timeframe of a project (such as 6-12 months).
    - Alternative use cases such as tool-wear could have been considered and might at least help validate the functionality of the software even if it is not the use case with the most business value.
    - The coolant /fluid monitoring prediction is another possible use case. which could have been considered for evaluating the functionality of the software and the integrated solution.

Recommendations:

- Select failure modes with faster degradation rates.
    - Selecting tool-wear or coolant as use cases for failure prediction might have addressed this challenge.
- Additional time and data for validating the health models and scheduling algorithm.
    - MXD projects could consider a more structured post-project support or evaluation phase. Alternatively, more time could be built into the project schedule for evaluating the system after it has been deployed.
- Evaluate technology and solution with other test-beds, including MXD facility and MXD member locations.
    - This evaluation of the technology at the MXD facility is already in the planning stages.
    - The evaluation of the solution at other MXD member locations is of interest to the project team and would provide additional uses cases for further evaluation of the solution.

XI. ACCESSING THE TECHNOLOGY

The following software is required to provide the necessary inputs for this technology:

1. Predictive Maintenance Software
2. Shop Floor Management Software

The following data inputs are required for this technology:

1. Historical Machine Health Indices - the health indices for each monitored machine, from at least the last month. A health index should be provided from every day for each machine.
2. Scheduled Production Orders - start and end dates, PO numbers, and operations numbers for all scheduled orders for each monitored machine

Expertise required for implementation:

1. IT - needed to feed the required data inputs into the technology
2. Maintenance - end user and needed to input the maintenance parameters for each monitored machine component into the system. The predictive scheduler uses these parameters to calculate the optimal time to do maintenance.

XII. DEFINITIONS

JSON - JavaScript Object Notation

KPI - Key Performance Indicator

MES - Manufacturing Execution System

OEE - Overall Equipment Effectiveness

RUL - Remaining Useful Life

RM - Reactive Maintenance

PM - Predictive Maintenance

XIII. APPENDICES

Appendix A: Technology Integration

Deliverables:

- Module 1: Machine Health and OEE Integration
- Module 2: Predictive & Dynamic Scheduling

Scope of Near-Term Project Deployment:

- Continue to perform data analytics to validate the accuracy and value of predicting machine failures
- Evaluate effectivity of the scheduling module

Scope:

- Near term would be to deploy the application across 25-50 machines at the pilot manufacturing center.
- Long term would be to expand the deployment to multiple manufacturing centers.

Key Metrics: Operational:

Metric	Description	Target Value
Cost Reduction	Reduce spare part inventory and expediting costs	5-10% reduction
Machine Downtime	Reduce downtime on unplanned repairs	25-50% reduction
ROI	Cost Reductions/Costs of Implementation	

Plan to Scale:

- Expand machine monitoring across common machines classes to broaden analytics database. Validate predictions to actual machine failures. Track maintenance cost and time to repair to validate reductions, 1-3 years
- Expand machine monitoring to new machine classes, 2-5 years

Additional Target MxD Members:

- Any industries with significant capital investments in industrial equipment and high recurring maintenance expenses would benefit from this technology