PREDICTIVE MAINTENANCE PRACTICES & STANDARDS

by

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LIST OF ABBREVIATIONS

ADM: Absolute Distance Measuring

API: Automated Precision Incorporated

BCU: Bearing Condition Unit

CBM: Condition-Based Maintenance

CMM: Coordinate Measuring Machine

CNC: Computer Numerical Control

ERP: Enterprise Resource Planning

EWO: Emergency Work Order

FCA: Fiat Chrysler Automobiles

HMI: Human Machine Interface

IFM: Interferometer

IoT: Internet of Things

MES: Manufacturing Execution System

PAP: Predict and Prevent

PdM: Predictive Maintenance

PLC: Programmable Logic Controller

PM: Preventive Maintenance

RPM: Revolutions Per Minute

RTU: Remote Terminal Unit

SCADA: Supervisory Control and Data Acquisition

SEA: Spindle Error Analyzer

WCM: World Class Manufacturing

GLOSSARY

Asynchronous Error: Spindle Error that does not include integer multiples of the rotational frequency, but all other frequency errors, for example, spindle bearings. (Lions Precision, 2017)

Hysteresis: Referring to pressure or thermal sensors hysteresis is the acceptable range of a sensors capability to monitor and record. (Ifm Efector 2019).

Industry 4.0: "4th Generation Industrial Revolution based on Cyber-Physical System-enabled manufacturing and service innovation" (J. Lee, H. Kao, & S. Yang, 2014).

Laser Tracker: Portable coordinate measuring instrument that is often used to measure machine geometry due to its size and flexibility (R. Acero, J. Santolaria, M. Pueo1 & A. Brau, 2015).

Machine Health Checks: Health assessment can be performed by using a data-driven algorithm to analyze data/information collected from the given machine (J. Lee, H. Kao, & S. Yang, 2014).

Multi Axis Laser: "A multi-dimensional laser measurement system that simultaneously measures linear, angular, straightness and roll errors for rapid machine tool error assessment" (Automated Precision Incorporated, 2018)

Preventive Maintenance: Implements preventive maintenance on equipment at fixed periods in time, for example, monthly filter changes (Y. He, C. Gu, Z. Chen, & X. Han, 2017).

Reactive Maintenance: It is used to restore the operating state of the equipment after failure occurs (Y. He, C. Gu, Z. Chen, & X. Han, 2017).

Smart Machines: Being able to assess the current or past condition of a machine, using established communication protocols, Internet of Things devices, and the Cloud to enable life cycle cost reductions and machine performance improvements (Machine Design, 2013).

Smart Sensors: Smart sensors make machines self-aware. Smart sensors contain Internet of Things technology, which enables the sensor to communicate data, allowing machines to operate more effectively (Rockwell Automation 2018).

Synchronous Error: Spindle error that does not synchronize with rotation speed, integer multiples of the rotational frequency often referred to as average error (Lions Precision, 2017).

ABSTRACT

Manufacturing today is increasingly competitive and every organization around the world is looking to decrease costs. Maintenance costs generated an average of 28 percent of total manufacturing cost at the Fiat Chrysler Indiana Transmission Plant One in 2018, states Rex White, Head Maintenance Planner at Fiat Chrysler (2018). Maintenance is a supportive expense that does not generate a profit, which makes maintenance an attractive expense to decrease. The cost for components and skilled labor are expensive; however, the downtime is exponentially a larger threat to production cost. One most feared scenarios within a manufacturing facility is that one machine takes down several as it backs up the entire production process.

The three major types of maintenance are reactive, preventive, and predictive. The research project focused on applying the principles of predictive maintenance to the Fiat Chrysler facilities in Indiana. The report explains the techniques and principles of applying the technology currently available to reduce downtime and maintenance cost. The predictive maintenance procedures and saving are compared with reactive and preventive methods to determine a value of return. The report will examine the benefits of using the Internet of Things technology to create autonomous self-diagnosing smart machines. The predictive maintenance plan in this research illustration will introduce health check equipment used to implement longer lasting machine components. In conclusion, the project developed out an entire predictive maintenance plan to reduce downtime and maintenance costs.

CHAPTER 1. INTRODUCTION

Maintenance is an essential segment of all things that use mechanical or electrical components. The manufacturing world relies on equipment to produce products. Mechanical and electrical equipment efficiency relies on proper maintenance practices. Maintenance is a broad term covering many applications, for example, preventive maintenance, reactive maintenance, and predictive maintenance (Y. He, C. Gu, Z. Chen, & X. Han 2017).

Fiat Chrysler in Kokomo and Tipton, IN has four facilities, the smallest being 160,000 square feet and the largest at 3.1 million square feet of covered floor space. The facilities offer machining of engine block castings and transmission components (aluminum and steel); transmission assembly. Fiat Chrysler is a transportation manufacturing company that follows six sigma and lean manufacturing processes and is considered a world class manufacturer (Bob Vavra, 2016). Assembly lines, machining lines and casting lines run 24 hours a day, five days a week with opportunities for weekend hours.

Maintenance procedures are set as reactive maintenance with planned preventive maintenance schedules. Reactive maintenance focuses on fixing equipment after a failure has occurred creating downtime for repairs. The cost of downtime is related to the dollar amount of parts, production loss, direct and indirect labor. Direct labor cost will be the amount of time maintenance is working on the equipment. Indirect cost will be operators waiting on product to perform their responsibilities. The Fiat Chrysler assembly line has a window of ten minutes before the next operation can be taken down by the previous operation. Preventive maintenance procedures are set in place to assist in avoiding downtime. A schedule is in place to inspect equipment for loose electrical connection, filters, cleanings, air, hydraulic lines, and inspection of wires. These procedures also schedule component replacements, for example, electric motors and switches. The components are often still working and are replaced for a just in case scenario.

Preventive maintenance will decrease downtime by means of upkeep and replacing parts. However, preventive maintenance often leads to replacing parts that may still be in good working condition, which can create additional costs (Y. He, C. Gu, Z. Chen, & X. Han 2017).

Reactive/corrective maintenance is fixing or replacing components after detection of a failure. Reactive maintenance is an unavoidable cost for management of assets, however; it will be reduced by means of predictive maintenance practices and standards.

Predictive maintenance produces a forward-thinking concept to upkeep and repairs. Predictive maintenance will give a facility the ability to increase equipment reliability, productivity and reduce the overall maintenance cost. Equipment failure will be reduced by collecting data on the equipment’s performance to better detect future failures. The data collected can be graphed to produce a performance chart when equipment is running at peak performance building a footprint of the equipment. The footprint can then be periodically analyzed to determine if components have changed through physical alteration or internal damage providing data history capability for compliance reporting (J. Lee, J. Ni, D. Durdjanovic. H. Qiu, & H. Liao, 2006).

Fiat Chrysler does not have predictive maintenance procedures being utilized in the four facilities in Indiana. Fiat Chrysler is currently researching techniques and equipment available to generate a successful predictive maintenance program. Research has shown emerging and innovative technologies that have been conceived through the Internet of Things (IoT) is a game changer. Internet of Things technology that is focused on predictive maintenance concepts and practices will assist in collecting useful data.

STATEMENT OF PROBLEM

There will always be a need for maintenance in a manufacturing setting. Mechanical and electrical systems break down due to wear from friction and environmental corrosion. The past maintenance mentality has been directed to the "fixing it" process. However, due to innovative intricate technologies, waiting for breakdowns is a slow and expensive maintenance practice. Predict and Prevent (PAP) principles (J. Lee, J. Ni, D. Durdjanovic. H. Qiu, & H. Liao, 2006) are efficient and will reduce expensive downtime during maintenance processes.

Unplanned downtime is expensive. For example, at Fiat Chrysler assembly downtime can range from $300.00 to $400.00 a minute states Bruce Frytz (2018 October 14), supervisor of the Fiat Chrysler maintenance assembly team. Costly downtime will add increased pressure upon maintenance to make fast repairs or "bandages" to keep machines running and product moving. Preventive maintenance programs are in place to reduce the amount of downtime. Predictive maintenance can be the least intrusive and diminish downtime exponentially (Machine Design, 2013).

Imagine a machine that provides data offering trend charts or hysteresis measurements illuminating the health condition of the mechanical and electrical components. Procedures can be put into practice that will divulge the condition of mechanical components without disassembling one component on the machine (Keith Mobley, 2002).

The Internet of Things has allowed the development of innovative technologies. Smart sensors combined with communication devices have taken predictive maintenance to a new level allowing machines to collect and communicate valuable information.

According to Parpala and Iacop (2017) predictive maintenance is centered off of Condition-Based Maintenance (CBM) with three primary phases. Steps include data acquisition, data processing, and maintenance decision making. The data is collected by using smart sensors that track the machines behavior and records changes over time. Smart sensors will allow the user to determine what may need to be replaced before it breaks down. Predictive maintenance combined with smart machines generates scheduled repairs rather than reactive repairs; thus reducing downtime and in turn increasing productivity (Parpala and Iacop, 2017).

The National Academy of Engineering Grand Challenges relies on machinery and maintenance. The grand challenge involving fusion generators will need robotics and a variety of mechanical working mechanisms to function (National Academy of Engineering, 2017). Predictive maintenance will provide more reliable and stable equipment for manufacturing transportation products in urban advancements. Engineering tools for scientific discovery will depend on reliable and functioning equipment. Maintenance is a function of all moving parts and each grand challenge will rely on dependable equipment that will be maintained by a successful maintenance program.

RELEVANCE OF PROBLEM

Industrial manufacturing is a competitive market across the world. Systems have been experimented and implemented to save small and large amounts of manufacturing cost. Lean manufacturing, Six Sigma and World Class Manufacturing (WCM) are just a few of the programs that are being implemented in facilities across the world to become more efficient. Today’s competitive manufacturing environment has forced companies to look at new and revolutionary ways to become more proactive and improve performance and quality.

The developing standards for world class manufacturing have risen beyond reactive maintenance practices (J Lee, H. Kao, & S. Yang, 2014). Industry 4.0 will set new standards to better achieve efficiency in manufacturing processes.

Rex White, Head Maintenance Planner at Fiat Chrysler states that Chrysler's policy is to focus maintenance towards a zero breakdown concept at the lowest cost possible. The reduction in capital towards maintenance while focusing on zero breakdowns is a frustrating scenario. Maintenance managers are forced to look for new avenues to obtain corporate goals and policies. Rex states that in long term thinking, managers are focusing on the life cycle of the machine components by recording when a component is replaced. World Class Manufacturing maintenance principles focus on using Emergency Work Orders (EWO) (Appendix A) to determine the replacement cycle of machine components. The machine components are replaced as a preventive method, to replace the components before they break. Preventive methods lead to an increase in workforce, equipment cost and rely heavily on data collected over a large period of time (J. Vaidya, 2017).

The standard for a successful maintenance program is the reduction of downtime during production hours (Amman, 2018). Off time or nonproduction times are considered weekends or low production hours. Low production hours at Fiat Chrysler are considered weekends and third shift. The low production hours are when preventive maintenance is scheduled. The maintenance workforce is often increased during these hours to achieve machine component replacement and preventive checks. Preventive maintenance is comparable to replacing spark plugs in a vehicle every 50,000 miles. They may not need it; however, it may prevent a breakdown on the road.

Predictive maintenance will improve cost during low production times, increasing lengths between machine downtimes, and a reduction in the amount of time it takes to troubleshoot and repair machines (J. Vaidya, 2017). Predictive maintenance is using the condition of the equipment to schedule replacements of machine components. A predictive maintenance program will provide the least impact on production for repairs. (Parpala and Iacop, 2017).

CHAPTER 2. REVIEW OF LITERATURE

INTRODUCTION

Predictive Maintenance (PdM) is not a new practice. “William Murphy has worked with predictive maintenance since 1968, using vibration and balance rotation equipment”, states Richard Wilson, author of Establish a Predictive Maintenance Program at Hanford Site (1994) prepared for the Department of Energy found in the Purdue Library database. Wilson (1994) focuses on the early stages of portable technology available that could collect and save machine data. The infant stage of predictive maintenance was based on vibration analysis equipment that could record vibration results of machinery in excellent working conditions developing a footprint. The footprint would be used to retest periodically comparing the data to determine if equipment conditions had changed from wear or corrosion. Predictive maintenance has made many strides in technology and capability over the past two decades. The Internet of Things has revolutionized all industries, bringing in Industry 4.0. Bond (2017) stated in the article PwC and MAPI Release Survey on State of IoT in Manufacturing retrieved from the Purdue Library database.

“Thirty-one percent of manufacturers are implementing Internet of enhancements to their internal operations, with another 56% exploring, doing so to cut operational costs, achieve supply-chain efficiencies and improve predictive maintenance capabilities” (Bond, 2017 p.1). The Internet of Things provides a platform for supporting predictive maintenance goals in reducing cost and downtime frequency. The Internet of Things will deliver the ability for applications to receive information from multiple machines throughout a facility. Radu Constantin, Parpala, and Robert Iacob authors of “Application of IoT Concept on Predictive

Maintenance of Industrial Equipment" retrieved from the Purdue Library database refer to the IoT as a platform for a device to speak to one another (2017). The communication abilities of the IoT will allow machine sensors to communicate with a commercial or open source platform. Machine sensors can deliver data from the machine to a cloud platform. The data will then be viewed on a computer or any other communication device, for example, smart phones and tablets.

APPROACHES TO PREDICTIVE MAINTENANCE

"Predictive maintenance provides new opportunity to reduce the operational cost on equipment replacements and increase enterprises' economy" declares Meiling and Chen Liu authors of A Correlation Driven Approach with Edge Services for Predictive Industrial Maintenance (2017), retrieved from the Purdue Library database. Sensors, give the capability to monitor machines behavior or performance. Communication networking and data analysis technology, along with maintenance can become autonomous to generate information regarding the health status of a machine. This gives you the ability to predict failures before they occur (J. Vaidya, 2017).

Predictive maintenance has three approaches: analytical, model-based and hybrid methods (Meiling and Liu, 2018). The analytical approach is learning from new data, recording points of failures to set limits for future opportunities to repair before the failure occurs. The model-based approach is basing limits on alterations of change from the footprint of the machine. Hybrid method uses both, modeling the data from the machines best-running condition and updating the data over a set period of time. The hybrid method will generate a framework that will be able to predict when failure will occur (Meiling and Liu, 2018), and retain data to avoid prematurely replacing equipment. The combination of preventive machine upkeep and predictive analysis data can reduce downtime significantly more than either process by itself. Developing the mindset with the maintenance team that collected data through examinations, history and sensors is necessary to implement a successful program (J. Vaidya, 2017).

PREDICTIVE MAINTENANCE TECHNIQUES

Predicting failures can be done with many techniques and strategies. Maintenance strategy and quality production are connected. The more maintained the equipment is, the better chance at highly improving the quality of the product it produces. One technique of predictive maintenance is health checks. Health checks of a machine are scheduled checks by a trained technician using proper tools and equipment on essential components of a machine.

Predictive maintenance checks can restore and maintain a machine to near perfect running condition by controlling variables (Y. He, C. Gu, Z. Chen, and X. Han (2017). Recording the information collected during machine health checks and comparing new data to old data can divulge any changes in machine components while simultaneously improving the quality of the product produced by the machine. Literature is provided by companies for examining devices and developing manual health checks. Examples of machine tools used for health checks: are Automated Precisions Trackers, Renishaw Balbar and Lions Spindle Analyzer.

Smart machines designed from Industry 4.0 sensors and monitoring equipment have created a unified information grid of self-maintenance machines (Jay Lee, Hung-An Kao, and Shahn Yang 2014). There are a variety of brands of smart sensors, for example, Allen Bradley, Efector, Keyence, Mitsubishi, Siemens, Omron, Turk, Vydas, Honeywell, etc. For the purpose of this research project, literature will be reviewed from Ifm Efector Electronics and Keyence. Efector and Keyence were chosen for their working relationship already established with the Fiat Chrysler’s maintenance team in Kokomo Indiana. The project experiments will be done with the assistance of associates from both companies.

Sensors will fall in six categories: vibration, fluid, air, thermal, ultrasonic, and proximity. The vibration analysis will identify vibration patterns for machinery imbalance, bearing wear, misalignment and gearing distortion. Infrared imaging can identify high temperatures that could result in bearing issues, lubrication failure, and electronic contacts.

Flow and pressure sensors determine that lines are sealed and fluid is moving. The electric motor analysis will verify current loads and resistance. Ultrasonic sensors will check air and gas leaks and cracked lines.

Proximity sensors indicate the position of equipment, such as the homing position and the advanced or retracted position for fixtures. Placement of the sensor is important as well. Determining the optimal location for each sensor will provide “identification, structural control, damage detection, and structural health monitoring”, declares D. Borissova, I. Mustakerov, and L. Doukovska (2012) reported in the article Predictive Maintenance Sensors Placement by Combinatorial Optimization retrieved from the Purdue Library database.

The main objective for designing and implementing predictive maintenance producers is to meet production goals with the least interference from machine failures (M. Zhu and C. Liu 2018). The research from peer-reviewed articles and product information packets for equipment manufacturers will assist in developing a predictive maintenance plan. Fiat Chrysler will be introduced to the process of reexamining maintenance practices which will show machines quality capabilities. The Internet of things advantage will change the way machines are evaluated and repaired. Industry 4.0 will reduce labor costs and provide an innovative and supportable working environment (R. Morrar, H. Arman, and S. Mousa, 2017).

CHAPTER 3. RESEARCH METHODOLOGY

INTRODUCTION

Fiat Chrysler in Kokomo, Indiana started recruiting skilled trades in 2012 and still in 2019 the demand has not been met. The lack of workforce availability in maintenance and a growing demand for Chrysler products calls for new practices in maintenance. Predictive maintenance is an evolving trend in manufacturing of all areas according to Jay Lee, Edzel Lapira, Behrad Bagheri, Hung-an Kao (2014). The first step in research to developing a predictive maintenance program is determining the technology available.

Internet of Things has provided innovative ways for all things to communicate through the internet (R. Parpala and R. Lacob 2017). The Kokomo Transmission facility is applying world-class manufacturing to meet the needs of the consumer. The quality of the product and the process of manufacturing set the high expectations of upper management to constantly improve and adapt to a growing market. The cost of maintenance last year was over 28% of the manufacturing cost to develop the product says Rex White, Head Planner of Maintenance (2018, October 24) in a personal interview. The cost of maintenance includes lengthy downtime, equipment replacement, engineering, labor, quality improvements, and service support. The majority of the downtime cost ranges from $300.00 to $400.00 per minute unless a machine takes down the entire line, then it could cost thousands, states Bruce Frytz, 2018. The cost and inefficiency of the preventive and reactive maintenance programs are what drove the industrial 4.0 age to focus on predictive maintenance practices (Bond, 2017). Reducing downtime, increasing reliability and efficiency in maintenance and machine conditions are primary goals for a predictive maintenance process.

PREDICTIVE METHODOLOGY

Efector works with many facilities on applying and replacing new innovative sensors. Efector hardware and software will be used in the research for developing smart machines for predictive maintenance procedures and techniques. Ifm Efector's availability and willingness to assist has provided knowledgeable technical expertise with smart sensors has been an asset in determining the correct equipment. Sensors will include pressure, flow, depth, position, photo, vibration, temperature, and laser measuring sensors provided by Efector.

Smart machines will assist in collecting data on machine conditions by constant examination of bearings, spindles, ways, roller packs, ball screws, ball nuts, and position repeatability. Electrical systems of the machine will focus on current load and thermal reading to determine if current loads have changed and if connections have come loose. Keyence will provide the imaging sensors to examine thermal temperatures in machine cabinets. Servo drives will monitor motor temperatures, current loads, and speeds during operations.

The smart machine sensors will provide information on changes in the machine functions to prevent future failures and reduce unplanned repairs. Scheduled checks for recording data and machine examinations are protocol towards achieving a successful preventive maintenance program. Determining the capability to manufacture a quality product is related directly to predictive maintenance through maintaining machine health. Machine health checks will need to be developed using specialized equipment such as trackers, spindle analyzers, and axis laser. The equipment will be used to design footprints of machines to improve predicting failures and resolving them before they occur.

Geometric tools, for example, multi-axis lasers will be used to decrease wear and tear on machinery by alignment adjustments. Using a multi-axis laser to determine position movement and geometry of a machine will decrease defective parts and friction upon the equipment. Axis lasers will monitor position and geometric dimensioning of a machines axis while moving. Laser trackers offer the ability to check machine geometry and compare it to machine components, for example, squaring an axis to the movement of the spindle. Vibration equipment will record the footprint of the machines. Spindle analyzers offer a large window into the inner working of a spindle unit. The spindle analyzer will allow a true picture of a spindle condition without removing equipment or covers.

Determining an acceptable frequency for a machines health check is necessary for collecting data and comparing old to new data. Below is Figure 3.1, a rotation was developed for machine health checks to be done on a regular basis, depending on the constraint of the machine will determine the frequency. The machine health check will include the measurement equipment required, the machine number and manufacturer. Figure 3.1 includes machines in the red that will be considered overdue while the green shows the machine as up to date.

Machine Health Check Schedule				
				Updated 11/19/18
Case Line Machine #	Machine Type	Measurements Equipment Required	Completed Month / Year	Due Month / Year
AA111	Toyoda	6D-Geometry-SEA-Ballbar-Stotz	18-Sep	20-Sep
AA112	Fuji	6D-Geometry-SEA-Ballbar-Stotz	18-May	20-Apr
AA113	Fuji	6D-Geometry-SEA-Ballbar-Stotz	17-Mar	19-Mar
AA114	Fuji	6D-Geometry-SEA-Ballbar-Stotz	17-Dec	19-Dec
AA115	Felsomat	6D-Geometry-SEA-Ballbar-Stotz	17-Jun	19-Jun
AA116	Felsomat	6D-Geometry-SEA-Ballbar-Stotz	16-Jan	17-Dec
AA117	Toyoda	6D-Geometry-SEA-Ballbar-Stotz	18-Apr	20-Mar
AA118	Mazak	6D-Geometry-SEA-Ballbar-Stotz	16-Oct	18-Oct
BB252	Waldrich	6D-Geometry-SEA-Ballbar-Stotz	Dec-17	19-Dec
BB253	Waldrich	6D-Geometry-SEA-Ballbar-Stotz	18-Jul	20-Jul
Constraint Machines				

Figure 3.1 Machine Health Check Schedule

Figure 3.2 on page 13 and Figure 3.3 on page 14 are spreadsheets designed to record health check information. Keeping a record of machine health checks and results is a priority for data examination. Figure 3.2 displays a data sheet for a multi-axis laser machine health check. Tolerances for geometric dimensions are displayed by allowable error. The actual error is the recorded measured error found with the laser. The deviation is the amount of error that is higher than the allowable error. The data sheet is recorded and stored for future reference by machine number, axis measured and date.

Machine Number: AAA20634	Fuji CNC Z Axis Health Check			Date: 11/15/18
Equipment- Automated Precision 6D- Axis Laser				

Feature Measured	Acceptance Specifications and Results			Measurement Method and Equipment Used
	Allowable Error	Actual Error	Deviation	
Linear Accuracy	0.040	0.003		EQUIPMENT REQUIRED: API LASER
Bi-Directional Repeatability	0.040	0.002		Z AXIS MEASUREMENTS WILL BE TAKEN AT 50 MM INTERVALS MACHINE DWELL 10 SEC
Reversal error	0.020	0.025	0.005	DATA WILL BE TAKEN OVER 3 BI-DIRECTIONAL RUNS.
Z Axis Straightness X Direction	0.045 Max Travel	0.030		
Z Axis Straightness Y Direction	0.045 Max Travel	0.060	0.015	Note: Gibs need to be adjusted, and Backlash needs compensated due to Pitch, Yaw and Reversal error out of tolerance
Z Axis Pitch (Angle YZ)	15 arcsec Max Travel	17.0	2.0	
Z Axis Yaw (Angle XZ)	15 arcsec Max Travel	16.0	1.0	
Z Axis Roll (Angle XY)	15 arcsec Max Travel	8.0		
Inspected By:		Date:	Control Compensation Used	

Figure 3.2 Multi Axis Laser Health Check Data Sheet,
Larger Image Appendix B

Figure 3.3 is one example of a spindle analysis data sheet. The data sheet relays information about each machine. Figure 3.3 displays Revolutions per Minute (RPM) that will be determined by the max RPM value for each machine. Every spindle will be rated at 10%, 50% and 100% with an allowable error determined by each spindle manufacture. Figure 3.3 includes the asynchronous error and the average error. Synchronous error or average error is the motion of error synchronized with the rotation of the spindle. Asynchronous is an error that does not sync up with rotation, for example, a flat spot in a bearing would increase this reading.

Machine Number AA479	Toyoda Spindle Unit			Date: 11/15/18
Spindle Analyzer Setup Illustration				

RPM	Allowable Error	Measured Error	Deviation	Spindle and Measurement Description
	Spindle Unit Radial Error			
	Asyncronous Error Specifications and Results			
400 (10% rated rpm)	0.0040	0.0030		SPINDLE DESCRIPTION: Max RPM 4000
2000 (50% rated rpm)	0.0060	0.0020		
4000 (100% rated rpm)	0.0080	0.0160	0.0080	
	Average Error Specifications and Results			
400 (10% rated rpm)	0.0020	0.0010		EQUIPMENT REQUIRED: Lions Dynamic Spindle Analyzer 19-20mm Collet
2000 (50% rated rpm)	0.0040	0.0030		
4000 (100% rated rpm)	0.0050	0.0030		
	Spindle Unit Axial Error			
	Asyncronous Error Specifications and Results			
400 (10% rated rpm)	0.0040	0.0020		
2000 (50% rated rpm)	0.0060	0.0010		
4000 (100% rated rpm)	0.0080	0.0010		
	Average Error Specifications and Results			
400 (10% rated rpm)	0.0020	0.0001		
2000 (50% rated rpm)	0.0040	0.0010		
4000 (100% rated rpm)	0.0050	0.0010		
Inspected By:			Date: 11/15/18	
□				

Figure 3.3 Spindle Health Check Data Sheet, Larger Image Appendix C

IMPLEMENTATION PROCEDURE

The following implementation plan/procedure is original work developed with assistance from WCM, quality, engineering, and maintenance teams.

1. **Purchase Measuring Equipment**
2. **Skill Developments**
   - Automated Precision Inc. training laser tracker and 6D axis laser
   - SEA Lions spindle analyzer training
   - Renishaw ball bar training
   - Bruel and Kjaer vibration analyzer training
   - Keyence vision system training
   - Ifm Efector training for smart sensors
   - Parameter compensating training for controllers
   - Training in coordinate measuring machines
3. **Data Retrieval**
   - Developing drive for predictive maintenance recordables
   - Developing excel sheets for health check rotation
   - Developing health check records and machine tolerances
   - Building network drives to store and receive smart sensor data
   - Building initial data for machine footprint.
4. **Upgrade Machines with Smart Sensors and Control Configurations**
   - Determine starting point machine/line
   - Set time frame for installation
   - Install smart sensors
   - Install communication and smart controller
5. **Programming**
   - Program machine controllers
   - Program smart controller to record sensor data and store in predictive maintenance drive
   - Generate computer numerical control programs for health check equipment
6. **Results**
   - Examine documented results in cost saving
   - Examine document quality improvement
   - Examine scrap reduction
7. **Purchasing New Equipment**
   - Setting up purchasing agreements for future machines to meet predictive maintenance standards

DEFINING RESULTS

Researching and deciding on proper equipment for smart machine sensors, network, and software will be the first step in a successful predictive maintenance plan. Ifm Efector has smart sensors for all avenues of manufacturing, implementing the correct sensor for the right process is key to achieving machine reliability. The correct smart sensors will offer acceptable feedback time, ranges, digital displays, and network communication capabilities. Defining the correct vision system with the appropriate capabilities to meet the needs of each machine and maintaining the same software and company will need to be achieved. Keyence offers a variety of vision system to choose from; finding the correct one for the Fiat Chrysler facility will assist in defining smart machine results. Machine health checks will rely on precision instruments to achieve zero downtime goals.

Properly used predictive maintenance will improve all aspects of improving efficiency and reliability (Amman, 2018). Successful implementation will display a reduction of unplanned maintenance repairs. This will reduce the cost of replaced machine components, by decreasing damage and identifying issues before failures occur (M. Zhu and C. Liu 2018). Mechanical failure due to friction and wear, if detected early, will prevent major repairs. Quality improvements on a product will increase due to geometry adjustments being made to avoid wear from friction. Scrap will decrease due to the constant monitoring of sensor data and machine geometry checks. The overall reduction of maintenance costs will be revealed within the first year of implementation. “Sensors and instrumentation are central driving forces for innovation, not only for Industry 4.0, but also for other megatrends that are described with the adjective smart, e.g. smart factory, smart production, smart mobility, smart home, or smart city” (A. Schütze, N. Helwig, and T. Schneider, 2018 p. 368).

CHAPTER 4. RESULTS

INTRODUCTION

Developing a foundation for predictive maintenance is the means for successful implementation. Deciding on the correct equipment will be the first step to developing a strong foundation platform for a predictive maintenance plan (M.T. Dulman and S.M. Gupta, 2018). Mentioned in previous pages, Ifm Efector and Keyence have been two companies' that have been assisting in developing a plan for the correct sensor and vision systems. Developing the correct plan and equipment will be the first step in initiating interest in a predictive maintenance program among executives. Understanding smart sensors capability and limitation is a significant part of choosing the correct sensors (M.T. Dulman and S.M. Gupta, 2018). To implement health checks successfully standards must be met with equipment able to achieve the goals of a predictive maintenance plan.

The Fiat Chrysler company and associates developed the WCM practices in 2005 (B. Vavra 2016) to improve maintenance and manufacturing procedures. The development of a team of individuals that offered a technical perspective was an important factor in the implementation process. The predictive maintenance team involves WCM focused engineering, maintenance technicians, supervisors, and planners. The system developed from the research was examined and resulted in a determined approach of implementation that meets Fiat Chrysler needs. Developing a set of standards alters at each facility. Decisions depend on mathematical models and the available skill sets of maintenance technicians in each department or facility. (H. Wang, X. Ye and M Yin, 2016)

World Class Manufacturing in February, 2019 focuses on preventive methods based on planning for equipment to be replaced by measuring the past failures periodically. Predictive maintenance will focus on analyzing equipment behavior rather than components life span. Predictive maintenance predicts failures by examining the data collected through sampling points over time and comparing them to initial equipment readings. (H. Wang, X. Ye, and M. Yin, 2016).

SMART SENSORS

Flow Sensors

Predictive maintenance data is assessing the current data and data collected over time of the equipment operations (H. Wang, X. Ye and M Yin, 2016). Data is collected through smart sensors, for example, flow sensors that monitor the flow of fluid. Ifm Efector flow switch SM series in Figure 4.1, is installed on every lube line throughout the machine. “The conductive medium flowing through a pipe in a magnetic field generates a voltage that is proportional to the flow velocity” (Ifm Efector, n.d., p.4). The flow switch allows data to be collected and recorded for lube and fluid trends.

The SU series ultrasonic flow sensor offers a temperature sensor as well (Efector n.d.). The SU series will work with coolant lines, for example, high-pressure spindle coolants. The unique feature of temperature measurement, as well as the flow, will be perfect for coolant applications. Monitoring coolant temperature at a machining position increases precision by reducing thermal growth. Figure 4.2 is an image of the SU series ultra-sonic flow sensor with display module for flow and temperature readings.

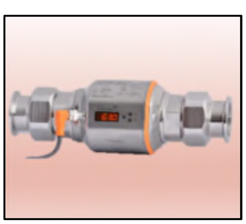

Figure 4.1 Ifm Efector SM Flow Sensor (Ifm Efector, n.d.)

Figure 4.2 Ifm Efector SU Flow Sensor (Ifm Efector, n.d)

Level Sensors

Ifm Efector level sensor LT series seen in Figure 4.3. They offer integrated temperature monitoring as well as level monitoring (Ifm Efector, 2019). The smart level sensor will monitor the level of a fluid tank and the temperature for best practices of machine coolant monitoring. The level switch will offer adjustable probe levels for emersion depth monitoring. Combining temperature and level of fluid will reduce holes in tanks.

The number of sensors will be reduced due to the option for maximum and minimum levels with one sensor (Ifm Efector, 2019). The sensor will be used to maintain coolant levels for filter systems and machine cutting coolant. Machining metal will create thermal growth that could lead to an out of tolerance product. The temperature feature will assure that the coolant maintains set temperature to reduce thermal growth during the machining process.

Industrial scenarios do change for each machining process. A scenario in which a level sensor is needed that has no influence from foam or temperature, the Ifm Efector PY/PN series is available. The PY/PN series level sensor is a high precision level design for industrial environments (Efector, 2019). The PY/PN series seen in Figure 4.4 exhibits a more rigid design with a display unit. The PY/PN series uses analog outputs to provide an effortless examination of trends.

Figure 4.3 Ifm Efector LK Level Sensor (Efector, 2019)

Figure 4.4 Ifm Efector PY/PN Level Sensor (Efector, 2019)

Pressure Sensors

Ifm Efector offers a variety of pressure switches. The one that displays the most robust construction and efficient response times is the PN series switch. The PN series pressure and vacuum sensor seen in Figure 4.5 is used for both hydraulic and pneumatic applications (Ifm Efector, n.d.). The PN series sensor is a solid state sensor, using no moving mechanical parts. The PN series offers multiple set points and is structured for trend data monitoring. Pressure sensors are used for air and hydraulic supply lines to machines. The sensors are constantly monitored through the machine's programmable logic controller. Trend data is networked for examination periodically highlighting any significant changes.

Ifm Efector has design specific pressure sensors for pneumatic application in robotics. The PQ series pressure switch is smaller and costs less than its PN counterpart (Efector, n.d.). The design is compact with a display unit as seen in Figure 4.6. The PQ series does not offer the rigid design the PN series offers and is best used in clean environments without contamination from fluids. The PQ series is not a switch, it is a sensor that provides recordable data trends and a display unit to see pressure values. The PQ is easily programmed with a two button display or Efector's parameter software. The PQ series can measure vacuum as well as pressure much like its counterpart the PN series.

Figure 4.5 Ifm Efector PN Pressure Sensor (Efector, n.d.)

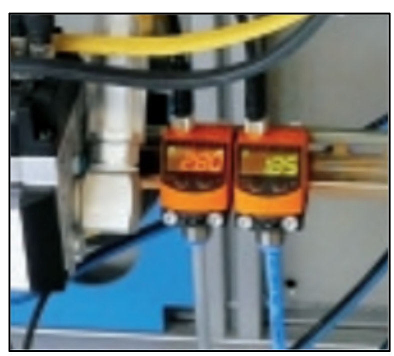

Figure 4.6 Ifm Efector PQ Pressure Sensor (Efector, n.d.)

Temperature Sensor

High-pressure temperature sensors for hydraulic machine settings can reveal mechanical wear or binding in a machine. Ifm offers the TR series temperature sensor constructed for industrial applications (Ifm Efector, 2019). The sensor is all solid state with a digital display as seen in Figure 4.7 The pressure sensor has an adjustable probe with broad ranges in temperature and pressure settings. The TR series is set up effortlessly for recording trend data while upkeeping real-time monitoring. The TR temperature sensor hysteresis window offers normally open and normally closed positions with the option for minimum and maximum temperature set points (Efector, 2019).

The zero set point can be set by calibration for more precise temperature readings. The temperature sensor is placed appropriately for each machine to monitor thermal changes in fluids. Fluid temperature changes that occur from extensively damaged equipment components. Example are components shavings in transmissions or spindles will increase the temperature of the fluid and can be found before significant damage occurs. The TR sensor holds a tolerance of +/- .3 Kelvin with measuring ranges from -40 to 150 Celsius (Efector, 2019). The TR temperature sensor is an elaborate device designed for recording data trends allowing fast access to live data. The setup for the sensor can be done through Efector's parameter software or using the buttons under the digital display.

Figure 4.7 Ifm Efector TR Series
Temperature Sensor (Efector, 2019)

Vibration Sensor

Vibration sensors are an imperative component for successful predictive maintenance practices. Ifm Efector has developed basic vibration sensors, intelligent vibration sensors with integrated diagnostic electronics, accelerations sensors, and software (Ifm Efector, 2017). Sensors are constructed to integrate monitoring, networking, and controllers.

Crash situations can result from a variety of causes; for example, wrong tooling, incorrect parameter settings and damaged components (Ifm Efector, 2017). Figure 4.8 is an image of an intelligent vibration sensor that can be easily placed throughout different machine components. The vibration monitoring will be integrated into a machine's control and networked to the facility server through field bus. Initial readings are used to develop threshold parameters for each individual machine. The sensor will continuously monitor and collect vibration data.

Figure 4.9 (Efector 2017) is an image displayed by an Efector vibration sensor threshold setting with vibration data collected. Figure 4.9 demonstrates how vibration trends and thresholds can detect or prevent mechanical damage to machine components. Figure 4.9 displays a nominal vibration reading with a rise in vibration before a crash situation. The machine can be set to give a warning message at the yellow line. The machine will shut itself down at the vibration limit in red (the alarm fault) reducing further damage.

Figure 4.8 Ifm Efector Vibration Sensor (Ifm Efector, 2017)

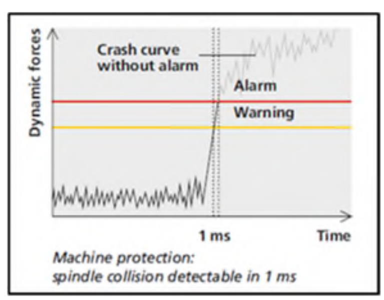

Figure 4.9 Ifm Efector Vibration Sensor Trend (Ifm Efector, 2017)

Monitoring Sensors

Ifm Efector has developed data logger equipment that can be easily networked through an ethernet interface. The device and software were developed to integrate with higher software, for example, Supervisory Control and Data Acquisition (SCADA) and Manufacturing Execution System (MES) (Ifm Efector, 2015).

The electronic diagnostic device is connected to a laptop or networks allowing more efficient troubleshooting at the machine location or a network accessible computer. The diagnostic device connects to the machines programmable logic controller, providing local faults and threshold monitoring. Figure 4.10 is an image of two types of electric diagnostic devices. The smaller version is for fewer inputs and outputs, when working with smaller machines. The larger diagnostic device offers more connections to smart sensors. Through the diagnostic device, parameters can be changed online or offline (Ifm Efector, 2015). The diagnostic device is a local hub of communication between sensors, programmable logic controller and networking software connections.

Figure 4.11 is displaying an example of how the electronic diagnostic device connects to the smart sensors. The smart sensors will send data to the diagnostic device and then disperse the information to the network remote terminal units (RTU’s) (Efector, 2015). The diagnostic device then directs data to the supervisory control.

Figure 4.10 Ifm Efector Diagnostic Device (Ifm Efector, 2015)

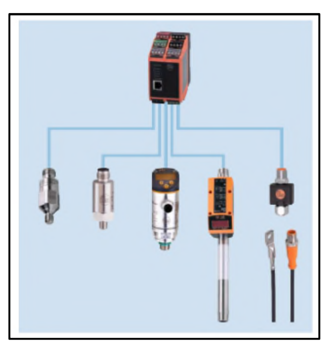

Figure 4.11 Ifm Efector Diagnostic Device Network (Ifm Efector, 2015)

Supervisory Control and Data Acquisition

The Supervisory Control and Data Acquisition system is used to employ a control system to monitor industrial machine components. Control systems involve the transfer of data between a control data acquisition, diagnostic device, central network (Appendix D) and a number of RTU's, (Lu Zhou, Chunhua Su, Zhen Li, Zhe Liu, and Gerhard P. Hancke, 2018). Figure 4.12 is an image example of how supervisory control and data acquisition software are working together to collect data. The IO-Link is the diagnostic device delivering information to the programmable logic controller and to the networked data acquisition software (Ifm Efector, 2016). The Enterprise Resource Planning (ERP) is the cloud-based storage center for the sensor collected data.

The supervisory control and data acquisition software formats the collected data with the ability to be viewed and used for diagnostic purposes. The ability to analyze and store the data separate from the machine creates a straightforward and fast process for parameter adjustments and a clear representation of the data (Efector, 2016).

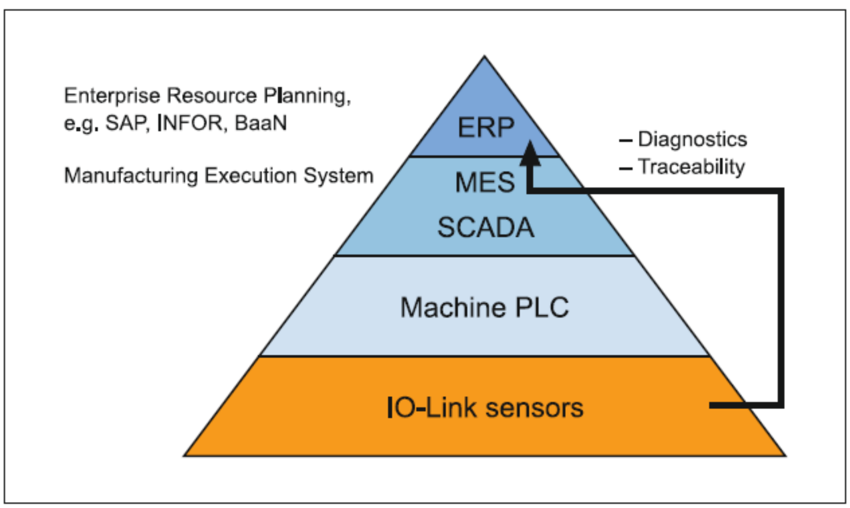

Figure 4.12 Supervisory Control and Data Acquisition Pyramid
(Ifm Efector 2016)

Keyence IV Vision System

Keyence IV vision sensor delivers a vision system designed for straightforward setups and programming. The IV vision series is compact with automatic adjustments offering a sensor robust enough for a manufacturing environment (Keyence, 2018). Figure 4.13 is an image of the IV vision sensor displaying two sizes. The two size are used to meet input and output requirements for multiple machine sizes. The compact vision system offers network connection and a programmable controller connection. The IV vision system can detect changes in pixels, shade, area, size, pitch, position edge counts and can be used as a two-dimensional scanner (Keyence, 2018).

The multitude of applications the vision sensor is capable of makes it an effective sensor for predictive maintenance requirements. The vision sensor is used for fixture features positions, part location, part type, tool size, and product quality. The two-dimensional scanning option is used for product serial codes to track part location and inventory in the facility. The Keyence IV sensor uses its own software for setup and programming, IV Navigator, which is formatted to work with all controllers and supervisory control data acquisition software (Keyence, 2018). The IV camera can be directly connected to computers and monitors for visual displays or networked through a facilities system to be monitored from a distance.

The Keyence vision sensor is the ideal vision systems for improving quality, inventory location and assists in achieving a successful predictive maintenance plan. Keyence has developed sensor heads that can be exchanged on the IV vision sensor to offer increased pixel definition and infrared imaging (Keyence, 2018).

Figure 4.13 Keyence IV Vision Sensors (Keyence, 2018)

Smart Machine Sensors

The combination of smart sensors and networking technology software provide the ability to continuously monitor the mechanical condition of a machine. Data is an important factor in manufacturing. Processes that use the data correctly can create efficiencies that drive more profitability per unit. The combined effort of smart sensors and communication devices create an abundant amount of valuable data that is readily accessible.

Moving forward in the experimental stage with the combined effort from Efector and WCM in 2018, a whiteboard was developed as seen in Figure 4.14. The whiteboard displayed pressure, flow, thermal, vibration and distance Ifm Efector sensors. The communication was set up to diagnostic devices with a small power supply composing all sensors to simulate as they would inside a machine. The whiteboard gave a unique perspective of a visual simulation to explain how all components work together. The goal was to demonstrate how clearly the data was collected and compared with prior readings. The demonstration revealed how efficient a machine can troubleshoot itself. The whiteboard displayed how data can be used to demonstrate a change in the working mechanisms to prevent major damage. The diagnostic device can be hooked up to a laptop with parameter software or communicate through a network for examination of data from a distance.

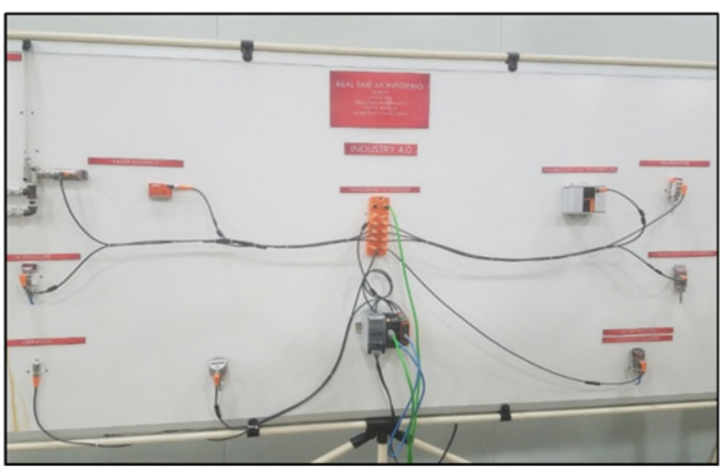

Figure 4.14 White Board Display of Smart Sensors
(FCA, 2019), Larger Image Appendix E

MACHINE HEALTH CHECK EQUIPMNET

Machine condition monitoring processes are driven by the intent to eliminate machine damage (National Instrument, 2017). Vibration, thermal measurements, noise, axis synchrony, and laser testing are used as decisive instruments to obtain the state of the machine. The machine health checks will be used accordingly with smart sensor data. The smart sensors detect a change in machines health conditions. The next step will be determining the cause of the change and what exactly needs to be done. Machine health check equipment is used to examine the machine anomalies and determine a course of action. A variety of actions can take place, for instance, making an adjustment, replacing components and adjusting mechanical positioning through control parameters.

The smart sensors will provide real-time data and identify that an anomaly is occurring with the machines running condition (National Instrument, 2017). The sensors will define what has changed, for example, a machine axis is found to be oscillating. This is caused by a faulty scale or bearings in a motor or ball screw. The sensors have identified the issue; next the health check equipment will narrow the possibilities to an exact condition. Figure 4.15 is a graph displaying warning signs of machines condition monitoring. The issue starts with vibration until the machine no longer is functional (National Instrument, 2017). Machine health check equipment will find the issue to the precise faulty component when vibration is detected by the smart sensors.

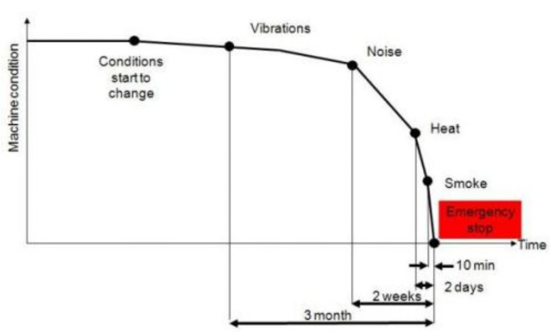

Figure 4.15 Machine Health Condition
(National Instrument, 2017)

Renishaw Balbar QC20-W

Renishaw's Balbar detects geometric errors, dynamic errors, positioning errors and axis play errors (Renishaw, 2019). The Renishaw Balbar software is designed to be compatible with most CNC controllers on the market. Installing is simplistic, set the Balbar between the spindle and an axis with a magnetically mounted fixture as seen in Figure 4.16. "The machine performs two consecutive circular arcs (clockwise and counterclockwise) in any one of the machines test planes (XY, YZ, ZX) and very accurately measures any variations in the test circle radius traced by the machine during the test" (Renishaw, 2013, p.8). The Balbar program will run three times, to calculate the repeatability of the test. The Renishaw software highlights readings that are not nominal, then software request to retest due to the high amount of anomalies found.

The Balbar than examines the data and develops a chart defining the error as seen in Figure 4.17. The chart displays error and the percentage of error that relates to the backlash, reversal error, positioning, and squareness for each axis. The Balbar QC20-W is a wireless tool that communicates through a Bluetooth connection with software installed on a laptop. The unique capabilities of the Balbar are not limited to determining where the error comes from.

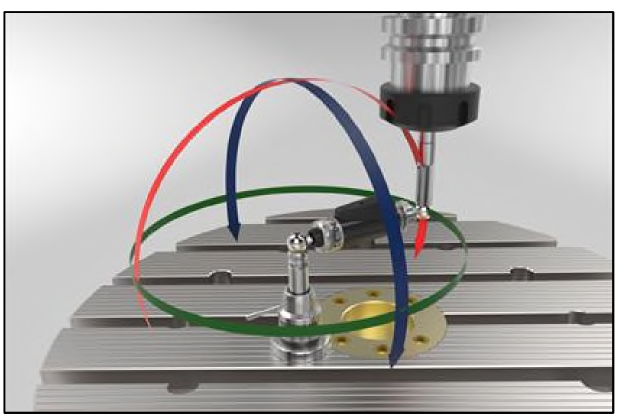

Figure 4.16 Renishaw Balbar QC20-W (Renishaw, 2019)

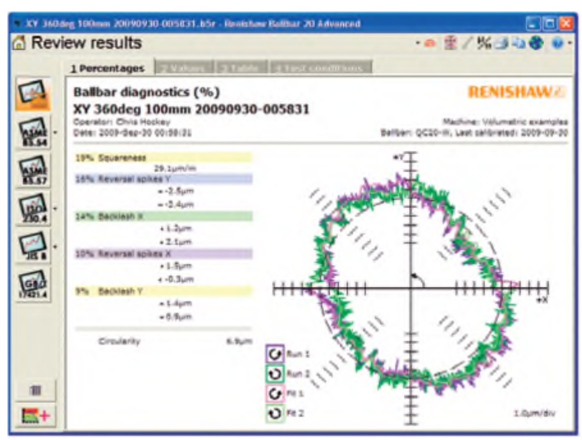

Figure 4.17 Renishaw Balbar Data Image (Renishaw, 2013), Larger Image Appendix F

The software additionally offers the capability of determining which machine parameters is adjusted to resolve the error. The parameter data is obtained by identifying the manufacturers' information, controller type, and the machine layout on Renishaw’s software. The software will write the Balbar program for the CNC to an extent of only a few program modifications for each individual machine by a programmer. The Balbar has a sensor resolution of one micron (Renishaw, 2013) making it a valid tool designed for interpreting machine error on behalf of predictive maintenance health checks.

Automated Precision Incorporated. Multi- Axis Laser XD6

The Automated Precision Incorporated (API) XD6 series laser has the unique ability to do all axis measurements in one setup, which separates this laser from others. The XD6 series offers the capability to measure flatness, parallelism, velocity, acceleration, repeatability, and position error in one setup for each axis (Automated Precision Inc, 2016). Figure 4.18 is a typical setup for measuring CNC machine axis with a multi-axis laser.

The CNC completes the program three times moving back and forth in increments on one axis. The laser will record each stopping point comparing all three runs to calculate the errors. The software VeriComp develops the number of position offsets needed to correct the position error. In Figure 4.19 is a screenshot of VeriComp software displaying the result of a linear position test. The machine alignment error will be calculated and separated into each type of error allowing the technician to determine if adjustments are needed. The receiver and the laser communicate wirelessly. The software communicates through Ethernet connections between laser and laptop.

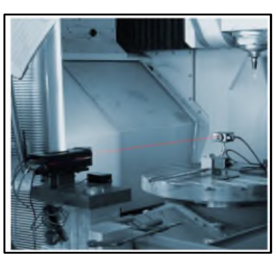

Figure 4.18 Multi Axis XD6 Laser (API, 2016)

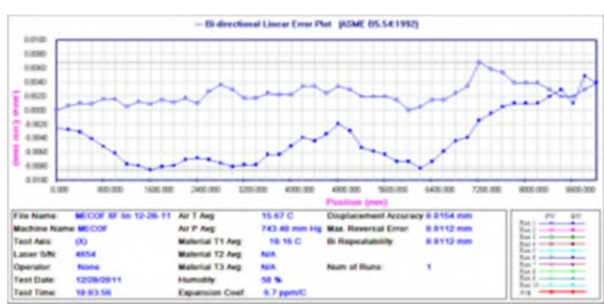

Figure 4.19 API Results Screen Shot (Total Machine Service n.d), Larger Image Appendix G

Automated Precesion Incorperated Radian 3D/6D Laser Tracker

The API Radian series laser tracker is the smallest and lightest tracker available today (Automated Precision Incorporated, 2016). The size and weight make the Radian tracker a valuable instrument in machine health checks due to its flexibility in small areas, displayed in Figure 4.20. The Raiden offers Interferometer (IFM) allowing precision measurements at longer distances and Absolute Distance Measuring (ADM) offering quick reconnection with no minimum distance (API, 2016). The Radian is the newest laser tracker available to offer both IFM and ADM.

The Radian allows the technician the ability to create three-dimensional digital drawings of an object with precise measurements using the Spatial Analyzer (SA) tracker software (API, 2016). Figure 4.21 is an image of a typical SA report. The report displays the image and the recorded measurements. The tracker is used for machine geometry adjustment to reduce strain on mechanical components. The Radian has the ability to precisely make fixture adjustments and measure repeatability, for instance, loading and unloading fixtures in a machine. The Radian is comparable to a portable CMM, which makes the API Radian useful in more than just predictive maintenance. The Radian can be used for part inspection, facility uses, and asset installs. Tolerances can be achieved with the Radian to the smallest of +/-.5 microns per meter (API, 2016) making it a reliable and precise measurement tool for maintenance and metrology alike.

Figure 4.20 API Radian Laser Tracker (API, 2016)

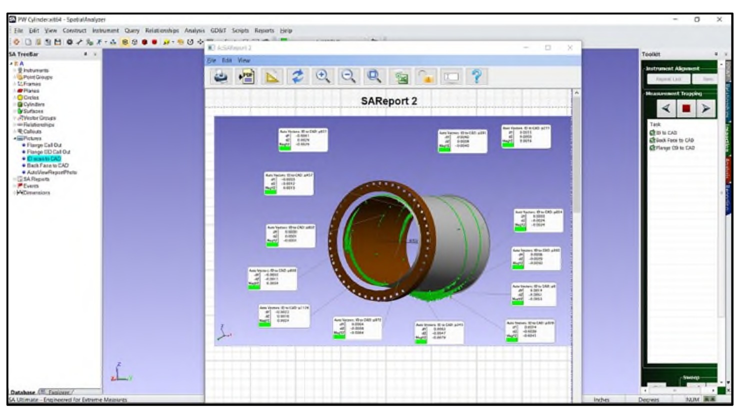

Figure 4.21 Spatial Analysis Report (New River Kinematics 2018), Larger Image Appendix H

Lions Precision Spindle Error Analyzer(SEA)

"The Spindle Error Analyzer System (SEA) is a hardware and version 9.0 software package for measuring and analyzing the accuracy of spindle rotation on machine tools, hard-disk drives etc." (Lions Precision, 2017 p.1). The Lions SEA offers both a five channel and three channel system.

The five-axis analyzer reduces the number of setups. The five channels offer measurements in all axis direction simultaneously. The five channel analyzer can be used with axis displacement sensors, temperature sensors and encoder sensors (Lions Precision, 2015). The ability to alter the setup on the five channel elite series gives the technician a multifunctional tool. When checking a spindle for error the five channel analyzer is set up with three axis direction sensors, and two thermal sensors. The three axis sensors and cards measure the axis displacement typically the X, Y and Z direction of the spindle. The thermal sensor will measure spindle change due to thermal growth from an increase in heat.

The SEA software is interpreted through imaging and numeric values allowing a trained technician to diagnose quickly. Figure 4.22 is screenshot of a one-micron scale result of a spindle bearing test. The screenshot displays the synchronous error, asynchronous error, total run out, RPM, machine name, channel number and an image of the measured spindle bearings (Lions Precision, 2017). The plot scale changes as the error increases, using the smallest scale

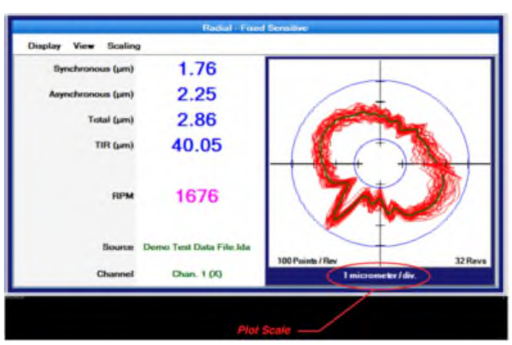

Figure 4.22 Lion's SEA Software Screen Shot (Lions Precision, 2017),
Larger Image Appendix I

needed to display the error. The plot scale can be manually changed as well for closer images if a technician finds the need to examine the test in smaller increments. The plot scale would be used for examining an error that does not show up on the graph, zooming in on the image to define if the damage is a bearing issue or a rotational error.

Figure 4.23 displays the five channel setup using an eight-slot enclosure and options for additional setups. The image in Figure 4.23 displays the flexibility and options offer with Lions Spindle Analyzer. The Lion's analyzer is robust for a manufacturing environment and easily setup inside a variety of machine structures.

The data retrieved from Lion’s analyzer can determine spindle damage and where the origins of the damage are internally. The analyzer provides run out data, bearing damage, and much more in a trivial amount of time in comparison to dismantling a spindle (Lions Precision, 2015). The flexibility and significant amount of data retrieved from Lion’s Elite Spindle Analyzer makes it ideal for a predictive maintenance health check.

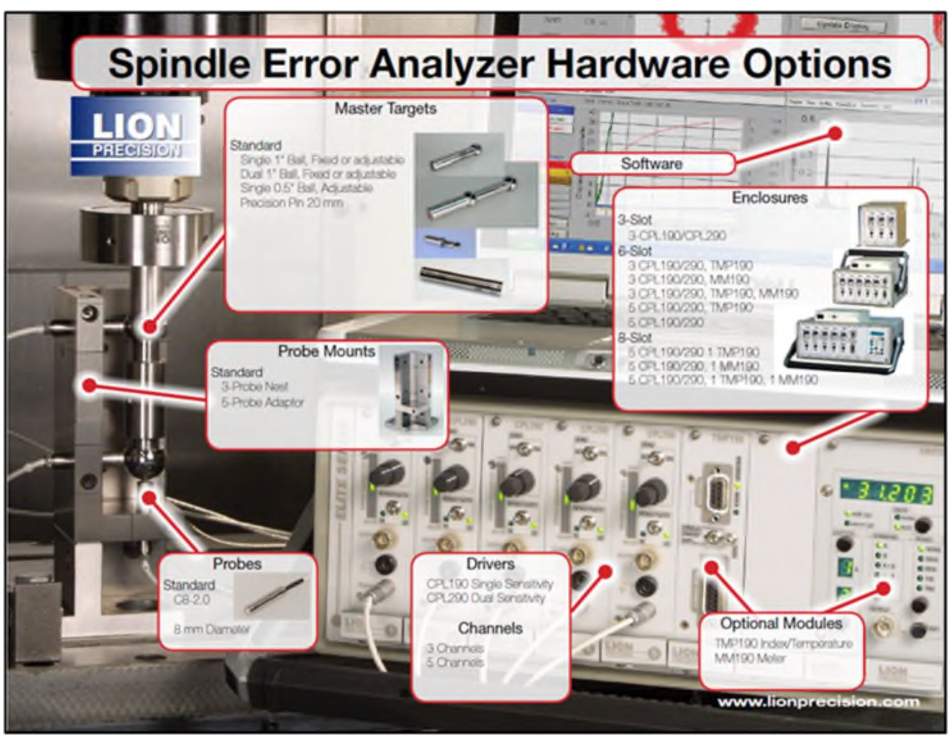

Figure 4.23 Lion’s Spindle Analyzer Hardware (Lions Precision, 2015)

Vibrotest 60

The Schenck Vibrotest 60 is a handheld vibration analyzer. The Vibrotest 60 offers the abilities of a vibration analyzer, data collector and field balancer (Bruel & Kjaer Vibro, n.d). The Vibrotest 60 offers absolute bearing vibrations, relative shaft vibrations, Bearing Condition Unit (BCU), band pass measurements, process values and speed measurement (Bruel & Kjaer Vibro, n.d). The Vibrotest 60 offers dual-channel vibration sensors offer the capability to inspect two positions rotor-synchronous vibrations, for example, examining a large rotating shaft (Bruel & Kjaer Vibro, n.d). The real-time data allows vibration to be examined in running conditions through coast positions allowing vibration measurements to record machines behavior.

The initial vibration readings are done when the machine is installed or all components have been inspected and cleared as working properly. The analysis will develop a footprint of the machine condition, for future examinations and health checks. The Vibrotest 60 unit in Figure 4.24 exhibits a handheld unit and a vibration sensor. The vibration sensors are magnetic and will mount to a clean metal surface of a machine component. The display size is adequate for viewing; the unit itself is light and can be held with minimal effort. The image displayed in Figure 4.25 is the screen on the handheld unit displaying a bearing test with two vibration sensors. The software for a technician's computer is Extended Monitoring Software (XMS) version 4.020. The image in Figure 4.26 is a screenshot of the software spectrum graph taken over a cycle. The software displays peaks of vibration during production process of a machine and is archived for future reference in a photo or video format.

Figure 4.24 Vibrotest 60 (Bruel & Kjaer Vibro, n.d)

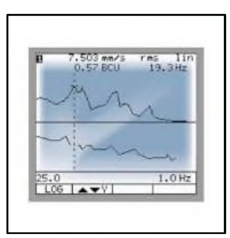

Figure 4.25 Vibrotest 60 Display (Bruel & Kjaer Vibro, n.d)

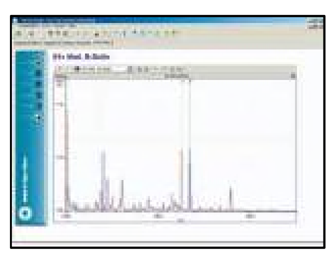

Figure 4.26 Vibrotest 60 XMS Software (Bruel & Kjaer Vibro, n.d)

Thermal Imaging Camera

The Fluke Ti450 features autofocus and has a built-in laser distance sensor that will display distances from the targeted device (Fluke, n.d.). The Fluke Ti450 is perfect for electrical cabinet inspection due to its point and click technology. The Ti450 offers a super-resolution that can produce four times the information to create a 640 x 420 image (Fluke, n.d). The Ti450 is efficient for on the floor maintenance inspections. Figure 4.27 displays the cameras design for handheld use with a display unit. The camera can be used to inspect cabinets for loose connections or bad contacts. The handheld unit can be used for a safety inspection before powering off machines to avoid arc flashing.

The Fluke Thermal camera uses a Fluke Smart Connect Software allowing images to be examined in a picture to picture mode (Fluke, n.d). The Fluke software displays before and after picture to examine side by side, making it efficient for troubleshooting. The software also provides the ability to document descriptions and other critical information with the image for future examinations. The smart view software saves data to the fluke connect cloud allowing all information transferred directly from the job site to the database. The size and durability of the camera combined with network capabilities and easy to use software makes Ti450 an excellent tool for predictive maintenance.

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Figure 4.27 Fluke Ti450 Infrared
Camera (Fluke n.d)

DATA STORAGE

To implement predictive maintenance effectively, manufacturing engineers will need to set the parameters of warnings and alarms for each machine (Ifm Efector, 2016). Implementing correct set points can be done through algorithms with autonomous maintenance. Engineering analyzes the captured data of the machine at best running condition and manually compares it to new data. Analytics can be applied to the machine data to predict conditions of a failure that may occur (T. Le, M. Luo, J. Zhou and H. L. Chan, 2014).

The collection of data is vast including sensor identification, machine data, sensor trends, health check equipment identification, software, dates, etc. The data is typically originating from sensors attached to programmable logic controllers that are networked to the facility's drives. The data is formatted through the company's SCADA to create data that is capable of being examined by technicians or machine learning algorithms.

Fiat Chrysler in Indiana has network drives for each of the transmission and casting facilities as of 2019. The network drives are expanded in terabyte increments to meet each facility's needs. The network provides all backups for CNC programs, machine ledgers, WCM data, machine history, and PLC programs. The network drive for each facility archives folders to store all predictive machine data. The smart sensor data is recorded and directly uploaded to the folder straight from the machine floor. The Microsoft Excel 2016 sheets and machine equipment software, for example, Renishaw's Balbar software and API multi axis software, are stored in the same department folder. The network drives can only be accessed from company computers with assigned asset tags/serial numbers for each folder.

The network drive includes all sensor information and health check equipment software, manuals, serial numbers, and calibration certifications. The originally designed certification spreadsheet will highlight red when equipment is past due for recertification and green when up-to-date. The health check equipment is sent out yearly for recertification and recorded on a spreadsheet as seen in Figure 4.28. The health checks are done yearly, recording machine information on spreadsheets similar to Figure 3.2 and 3.3 found on pages 13 and 14. Health check software files are stored and filed by machine number and date to create a retrievable archive of all the recorded machine data.

Machine Health Check Equipment	Serial Number	Last Certification Date	Due Date
Renishaw Balbar	145895676	1/10/2018	1/10/2019
Renishaw Balbar	1392940066	3/15/2018	3/15/2019
API Laser Tracker	4598-55	2/23/2018	2/23/2019
API Laser Tracker	4598-56	4/8/2018	4/8/2019
API Multi Axis Laser XD6	7936-12	2/23/2018	2/23/2019
API Multi Axis Laser XD6	7936-11	3/28/2018	3/28/2019
Lions Spindle Analyzer	3206-8146	5/6/2018	5/6/2019
Lions Spindle Analyzer	3206-8146	1/20/2018	1/20/2019
Schenck Vibrotest 60	23410879699	2/25/2018	2/25/2019
Schenck Vibrotest 60	17637600865	6/14/2018	6/14/2019

Figure 4.28 Health Check Equipment Certification Spreadsheet

VALUE OF RETURN

The research problem statement refers to reducing maintenance cost, downtime, and production increase through a predictive maintenance system. The Indiana transmission plant one (ITP1) has been the focus of much of the research. Through research and data comparing, a true interest has collected throughout the facility. Predictive maintenance programs have been implemented to improve maintenance cost; however, a true machine health program has not been established as of February, 2019. Machine condition programs that showed great potential have faded away through a lack of ability to provide and collect useable data to make improvements. The vibration unit mentioned prior has been used and displaced due to the lack of an evolving system that implements the tools and the ability to collect precise data. The lack of understanding restrictions and specification for each device was one of the downfalls. Additionally, there was a misunderstanding of how the separate equipment works together to complete a united representation of the machine's condition.

Tracey Aber, Indiana Transmission Plant one's (ITP1) Master Six Sigma Black Belt over the entire assembly maintenance division, took the time to meet on January, 30th 2019. Tracey went over examples of the 2018 overall machine efficiency chart (Appendix C). Mr. Aber explained how machine efficiency relates to tooling, supplies, chemicals, scrap, and maintenance. The efficiency of a machine is the first step, then defining what maintenance is and breaking down the individual elements to achieve cost reduction. Mr. Aber gave detailed explanations of what maintenance cost is by using the "Blue Room". The Blue Room was a large area separated by cubical walls displaying the cost of manufacturing and defined what each expense correlated to. Maintenance expenses were separated by efficiency, downtime, loss time, micro stoppages, etc.

The image in Figure 4.29 is a loss of productive time and cost chart for all machines at ITP1. Figure 4.29 indicates that micro stoppages are the second highest cost. Micro stoppages are considered faults that bring the machine down and the operator resets and runs. Micro stoppages are typically caused by one of the following issues, failing sensors, axis sloppiness, ball screw damage, scale or encoder issues, and high vibration states Mr. Aber. Smart machines record anomalies concerning all variables of the machine. The data would display a flickering sensor or any of the errors Mr. Aber stated, ultimately reducing micro stoppages at the first sign of an issue. The micro stoppage is a primary example of how predictive maintenance reduces production loss time and maintenance cost.

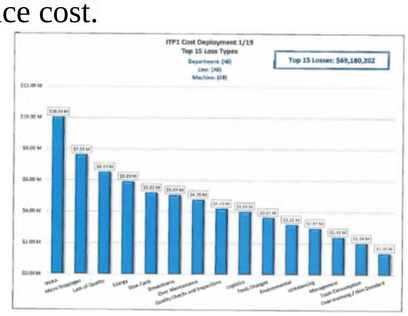

Figure 4.29 2018 Production Loss Time Chart (FCA, 2019), Larger Image Appendix K

The Image in Figure 4.30 is a manufacturing parts tracking system quality histogram, provided by Mr. Aber. The histogram is data from a machine recording how many parts are running at measured points within +/- 3 Sigma. The point at which the measurement leaves the bell curve is an anomaly. The anomaly displays change; in this case, it wasn't significant due to the small increments of the chart. However, the histogram divulges the effortless ability that goes into locating anomalies and identifying an issue (Abu Md Ariful Islam, 2017). Figure 4.30 is a sensor histogram identifying a flicker and calling for a replacement would end the micro stoppage error within minutes. The exact principle would work for a variety of errors, for example, position error, backlash, and looseness in an axis movement. The smart machine self-diagnosis displays enough evidence of the anomaly to request and perform a health check during a non-production weekend.

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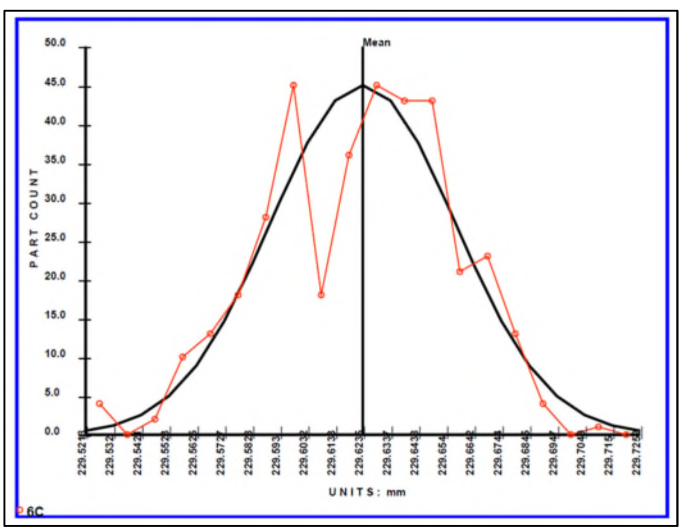

Figure 4.30 Manufacturing Parts Tracking System Quality: Histogram (FCA, 2019), Larger Image Appendix L

World Class Manufacturing held a meeting at FCA on January, 2019 focused on using preventive maintenance strategies. The WCM representative explained the average cost to run one machine for a year was $58,000.00. The WCM team focused on one machine and researched all the components that have been replaced in the last two years of production. The experiment was to replace all these components that had failed in the past at the beginning of the year 2018. The end result was an eight percent decrease in cost. The cost of running the machine in 2018 was less than the previous year. Including the additional purchases and replacement of all new components that may have been in good working condition, the experiment still showed a reduction in cost.

The report, The Internet of Things: Mapping the Value of Beyond the Hype, presented that predictive maintenance has the potential to reduce maintenance cost by 10 to 40 percent with a 50 percent decrease in downtime (McKinsey Global Institute, 2015). The eight percent decrease in the WCM experiment was achieved by avoiding downtime with no savings in machine components. Predictive maintenance strategy will increase the saving by eliminating unnecessary purchases of equipment while avoiding unscheduled downtime. Figure 4.31 shows a loss of time cost for the top 15 departments due to downtime for the year 2018 calculated to $54,997,897.00. A 50 percent reduction in all 15 departments of maintenance equals a $27,498,948.50, savings by reducing downtime during production hours. The capital spent on predictive maintenance equipment and strategies is inconsequential compared to the savings.

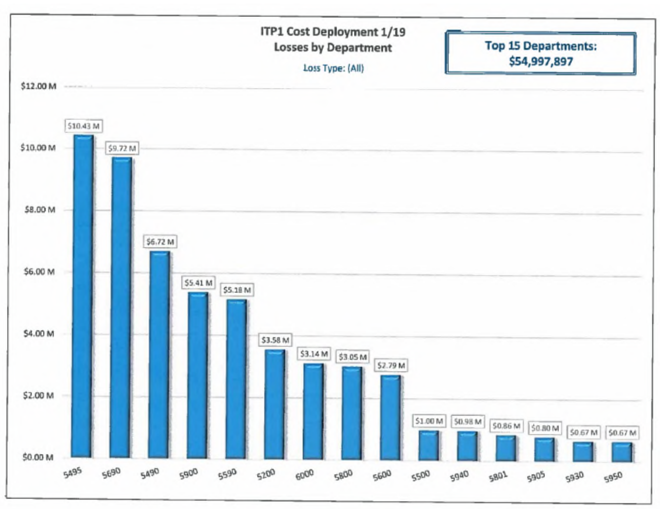

Figure 4.31 2018 Losses by Department due to Downtime (FCA, 2019),
Larger Image Appendix M

Figure 4.32 is original work displaying examples of three types of maintenance procedures. The example shows three scenarios examining the behavior of reactive, preventive, and predictive maintenance procedures. The first scenario is an example of reactive procedures of a ball screw failing. The machine will run until the ball screw can no longer move to the machine parameter settings. The result is replacing it and shutting the assembly line down for 24 hours, if all goes according to plan. The loss of production time is estimated at $248.00 per minute, this being at the low end of the spectrum for an assembly plant at Fiat Chrysler in Kokomo Indiana.

The second scenario is an example of a preventive maintenance procedure of replacing the ball screw yearly. The preventive maintenance procedure included replacing the ball screw during a weekend when production is not running. The preventive application does reduce loss time cost significantly. The ball screw replacement and alignment cost is calculated from the February, 2019 skilled labor rate at Fiat Chrysler Indiana facilities.

The third scenario provides an example of predictive maintenance procedures. The smart sensors warning displayed an increase in current or vibration on the axis months before the ball screw failed. The next step is to schedule a health check finding a miss alignment in the rails or roller packs. Thus, allowing an alignment adjustment to fix the issue with no increase strain on the ball screw. Predictive maintenance procedures greatly reduce equipment replacement and loss of labor cost. The scenarios demonstrated in Figure 4.32 display a significant savings by implementing a predictive maintenance plan.

Maintenance Procedures	Ball Screw Replacement	Loss Production Time	Ball Screw Cost	Alignment Adjustemt	Total Cost
SCENARIO 1 (Reactive)	16 Hrs.=1824	24 Hrs. = 357000	$2,200.00	8hrs = 912 Labor	$361,936.00
SCENARIO 2 (Preventive)	16 Hrs.=1824	0	$2,200.00	8hrs= 912 Labor	$4,936.00
SCENARIO 3 (Predictive)	0	0	0	8hrs = 912 Labor	$912.00

Figure 4.32 Examples of Maintenance Procedures and Cost

Mr. Brayden Lucas is a maintenance planner at the ITP1 facility in the 5495 department on January, 2019. Mr. Lucas gave the WCM team permission to do an experiment with a laptop, software and a CNC machine. The training exercise was to set the main disconnect settings lower than the current rating for the machine. The main disconnect would trip due to over current, the machine wasn’t being used for production so no loss time cost was contributed. Ten Electricians were assigned to the machine as a training exercise. Five were given a laptop to hook up to the main disconnect and monitor settings. Five others were given prints and a multimeter. The experiment was to see how long it took different electricians to find that the main disconnect was tripping due to the current limit settings. The experiment also supplied a good troubleshooting training event on the newer employees.

Figure 4.33 is an image of the roughly recorded results from the ten electricians on various shifts attempting to troubleshoot the machine. Figure 4.33 shows the amount of time it spent on troubleshooting the anomaly. The next column is the number of things tried to fix the issue, for example removing the disconnect cover, checking the contacts, checking resistance, or using a handheld amp meter. The final column is the results of finding the issue with laptop examining the live representation of the disconnect set points and amperage fluctuation. The results revealed that a picture is worth a thousand words. The five electricians found the issue almost immediately. The experiment was not an incredibly complicated; however, the experiment clearly displays a difference in the downtime between data-driven maintenance and reactive maintenance.

Maintenance Technician	Time on Issue (No Data)	Failed Attempts	Time on Issue (With Data)
Electrician 1	4 Hours	3	
Electrician 2	1.5 Hours	2	
Electrician 3	36 Minutes	0	
Electrician 4	2 Hours	2	
Electrician 5	6 Hours	5	
Electrician 6		0	5 Minutes
Electrician 7		0	3 Minutes
Electrician 8		0	3 Minutes
Electrician 9		0	3 Minutes
Electrician 10		0	2 Minutes

Figure 4.33 Main Disconnect Experiment

Figure 4.34 is a histogram similar to what the electricians saw when they hooked the laptop to the main disconnect. The rating was originally set at 80 amperages. The new setting was placed at 60 amperages. The moment the amperage reached over 60 amps the main disconnect tripped and shut all power off to the machine. The experiment was used as a training tool; however, it articulates a perfect example of data-driven predictive maintenance. The reduction in downtime is not from completely eliminating all issues with the machine components. The predictive maintenance tools create a more efficient source of troubleshooting. Micro stoppages often happen fast and can be complex happening within the minimum clock speed of a PLC. Timers are often as low as 150 milliseconds, examining many inputs and outputs simultaneously.

Figure 4.35 is an example of how a PLC program is using several inputs simultaneously to turn on an output. Figure 4.35 is one of many lines of logic in a working program. The image in Figure 4.35 is an example of how an input coming from a sensor could shut a machine down faster than a PLC could display it on a laptop. Smart sensors record data similar to Figure 4.34, where the anomaly was found promptly. Preventive maintenance equipment gives maintenance technicians a new advantage in resolving down machines more efficiently.

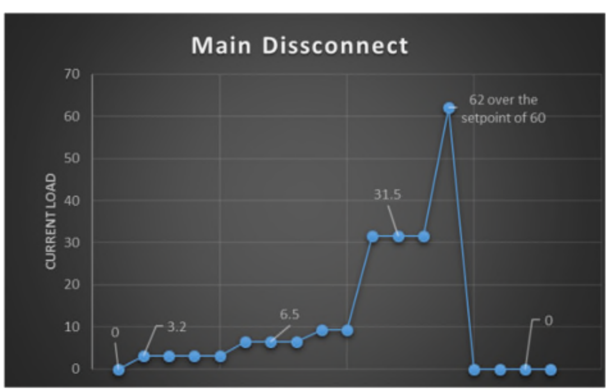

Figure 4.34 Main Disconnect Histogram

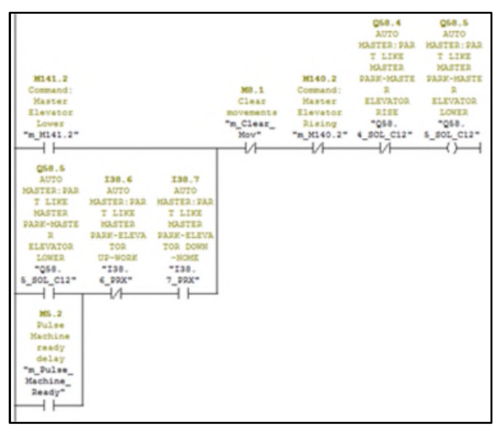

Figure 4.35 PLC Example

VERACITIES OF DATA

"One of the main goals of data science in this context is to effectively predict abnormal behaviors in industrial machinery, tools and processes so as to anticipate critical events and damage, eventually causing important economical losses and safety issues" (A. Diez-Olivana, J. D. Ser, D. Galar, and B. Sierrae, 2019 p. 92). Developing a predictive maintenance plan is a challenging hypothesis without all the equipment necessary to collect a large amount of data. The null hypothesis of this research is that predictive equipment does not reduce downtime or extend the life-cycle of equipment. The fact is that data creates a picture of a machine's health that aides in keeping machines at constant best working conditions.

The results define each piece of equipment that is used to develop a foundation for a machines condition. Using smart sensors and health check equipment creates a hybrid method of maintenance combining preventive and predictive attributes. Collected data with smart sensors generates a constant data stream of a machine's condition. Setting alarm points or using anomaly recognition algorithms gives the maintenance team a substantial advantage in troubleshooting machines. The machine health check equipment will allow a trained technician or engineers to examine machines internal components without removing covers or major components.

The data provided information through examples, visualization, financial gain, efficiency in troubleshooting and a true concept of the equipment's use. The one most difficult handicap in the implementation of predictive maintenance is assimilating the technicians to value the use of the data. The amount of machine data collected is large and from several pieces of equipment, the visualization and easy interpretation are factors to success (A. Ismail, H. Truong and W. Kastner, 2019). The predictive maintenance will be successful through transparency and training of the equipment used to achieve an efficient maintenance department.

CHAPTER 5. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

SUMMARY

Efficient equipment is one key to success for all engineering developments (National Academy of Engineering, 2017). Whether it be reducing carbon footprint through wind turbines, energy fusion, solar panels or reducing the manufacturing cost of with zero downtime. The true meaning of maintenance is increasing the life cycle and the reliability of equipment to produce an improved environment in everyone's day to day life. Predictive maintenance is the practice of developing a zero downtime environment for all mechanical moving devices (J. Vaidya, 2017). The primary goal of predictive maintenance is to "fix it" before it is broken.

Through the examination of maintenance procedures, the general consciences among manufacturing companies are that there is always room for improvement. Maintenance is much more than fixing machines as seen in the machine efficiency cost (Appendix J) and production lost time charts (Appendix K). Maintenance is responsible for quality, programming, tooling, design, energy efficiency, chemical cost, downtime and the overall well-being of all facility assets.

The example seen on page 41, Figure 4.33, is a table that shows a large reduction in time during the troubleshooting of a main disconnect through data driven maintenance. The reduction in troubleshooting and repairs is a potentially large costs saving for manufacturing companies. The ability to predict failures to reduce work stoppages and repairs during non-production hours is eliminating wasted time, which is a key factor in improving the process. Predictive maintenance offers a function requirement to the internal customer by reducing wasted time in the diagnosis stage setting a tone for success.

CONCLUSIONS

The research project has been informing in unexpected ways. The plan was difficult to focus in one direction with the amount of new technology available to achieve a predictive maintenance plan. The number of companies that offer smart sensors, machine conditioning equipment, and software was numerous and often overwhelming. The research project focused on companies that already had working relationships with FCA, this made retrieving research data more accessible. Fiat Chrysler is currently working through growing pains with WCM preventive/proactive maintenance procedures. The resistance from the maintenance technicians due to the extra paperwork involved in creating machine ledgers and EWO's has been a challenge. Introducing a new maintenance concept in the middle of an already difficult transition appeared to be impossible. However, after speaking to planners, supervisors, engineers and the WCM team it was encouraging how enthusiastic FCA’s management and engineering staff was involving predictive maintenance technology.

The assistance from my coworkers and superiors demonstrated how quickly the predictive maintenance plan was accepted. The support from technicians and supervisors, showed how predictive maintenance was more than a process. Predictive maintenance displays potential benefit for the company and all technicians involved. Indiana Transmission Plant One already had some of the health check equipment, that could have been used to create more data experiments to further develop the results section. Predictive maintenance technology is available in ways that have never been offered before (Mckinsey Global Institute, 2015). The vibration devices are small and easily placed throughout machine components for constant monitoring, for example vibration sensors have exponentially decreased in size just in the last couple of years (Ifm Efector,2017). Smart sensors have new communication capabilities due to the advancement of the Internet of Things, for example, the Ifm diagnostic device that communicates sensors and controls. Manufacturing equipment is networked allowing each machine to be monitored from a computer in an office a mile away. Machine health check equipment is smaller and more flexible making machine condition checks faster than in prior years.

Industry 4.0 is creating a more efficient manufacturing with increased communication abilities for manufacturing equipment. The predictive maintenance technology will be a significant part of Industry 4.0 in the coming years. Predictive maintenance will give the Industry the equipment reliability to make precise adjustments and track the feedback (Appendix L) in real-time. The smart sensors relay data that will improve process, quality and equipment reliability by increasing the ability to track multiple processes.

The intentions of the research project were to declare predictive maintenance as a solution to already rising maintenance costs in manufacturing. The results have shown that predictive maintenance technology goes much further than just reducing costs. Predictive maintenance begins with asset management which is a crucial subject in advanced manufacturing. Machinery is expensive in the initial stage of purchase followed by the rising cost of depreciation value of the asset. The technology available for predictive maintenance plan extends the life of the asset and reduces downtime. The mindset and tone of the project is important. Setting predictive maintenance up to improve internal functions through consistent training and ongoing practices will be detrimental to the program’s success. Predictive maintenance will present a display of forethought thinking to maintenance groups and technicians involved with highly technical machines. The training will increase the skilled labor work force efficiency in technical fields. The equipment used for predictive maintenance will improve process, and efficiency throughout the entire manufacturing process (Mckinsey Global Institute, 2015). Applying the equipment is a physical solution to meet the functional needs of a modern manufacturing environment. The WCM team is focused on continues improvement in all areas of manufacturing at FCA. The predictive maintenance program will implement continues improvements in the quality of product, reliability of equipment and improve data for machine ledgers.

RECOMMENDATIONS

Predictive maintenance procedures meet the criteria for a successful maintenance program by reducing maintenance cost and downtime. The research project results have displayed a new direction in which implementation process should change. Speaking with Tracey Aber (2019) FCA's Master Black belt divulged costs of equipment and training come into play when making investment decisions. Meetings with Ifm Efector, Keyence and API (2019) confirmed the costs for implementation would be exponential. The capital cost for smart sensors, software, and networking drive for a large manufacturing facility is significant, even with the proof of savings. The smart sensor prices range from $200.00 to $600.00 per unit and the vision systems can cost up to $3000.00 depending on the size of the unit. The networking and SCADA software implementation process is expensive as well. Health check equipment is only purchased once and can be used on all manufacturing assets; however, it is costly equipment with a lengthy learning curve. The tracker system price tag is over $100,000.00 per unit and the additional equipment such as stands and spherically mounted retroreflector can increase that by thousands. The spindle analyzer cost in the $50,000.00 range, not considering the sensors and the cards needed to perform an accurate test. The training in which one would have to undergo just to be adequate with the tracker is a long process. API suggested initial two-week training course and a return one-week training course a year after purchase.

The cost of equipment is miniscule compared to the savings as seen in the research project, there is a potential decrease in downtime by 50% with a 10% to 40% reduction in maintenance costs (McKinsey Global Institute, 2015). However, the initial cost can be a deterrent for many companies. The recommendation suggested in this research project is to separate the implementations of machine health check and smart machines. Although both health checks and smart machines are necessary tools to achieve an optimal predictive maintenance program. Introducing the combination of costs for both areas along with the amount of training needed is a difficult undertaking for any company to do all at once. The implementation process needs be slowly introducing a few pieces of technology at a time allowing the maintenance team to get on board and spreading initial cost over time.

Moving forward the research project needs altered the functional requirement of any manufacturing company is to continually improve. Continues improvement is motivated by employees and managers that are engaged within the company. The first step in the new process continuing forward is to create engagement within the maintenance, engineering and WCM teams. Building an application for each piece of technology. An example for this stepping process would be that the FCA facility has noticed a large amount of spindles have been replaced in the last quarter. The solution would be purchasing a spindle analyzer and training to prevent the spindles from going bad, after all each one is $36,000.00 and we have replaced six this year. Speaking with facility management, maintenance management, and WCM representatives (2019) this is a more appealing approach versus trying to purchase and implement all the equipment at once. The process would be done one piece of equipment at a time when there is ample justification for purchasing the equipment and the training to resolve an immediate issue that requires a physical solution.

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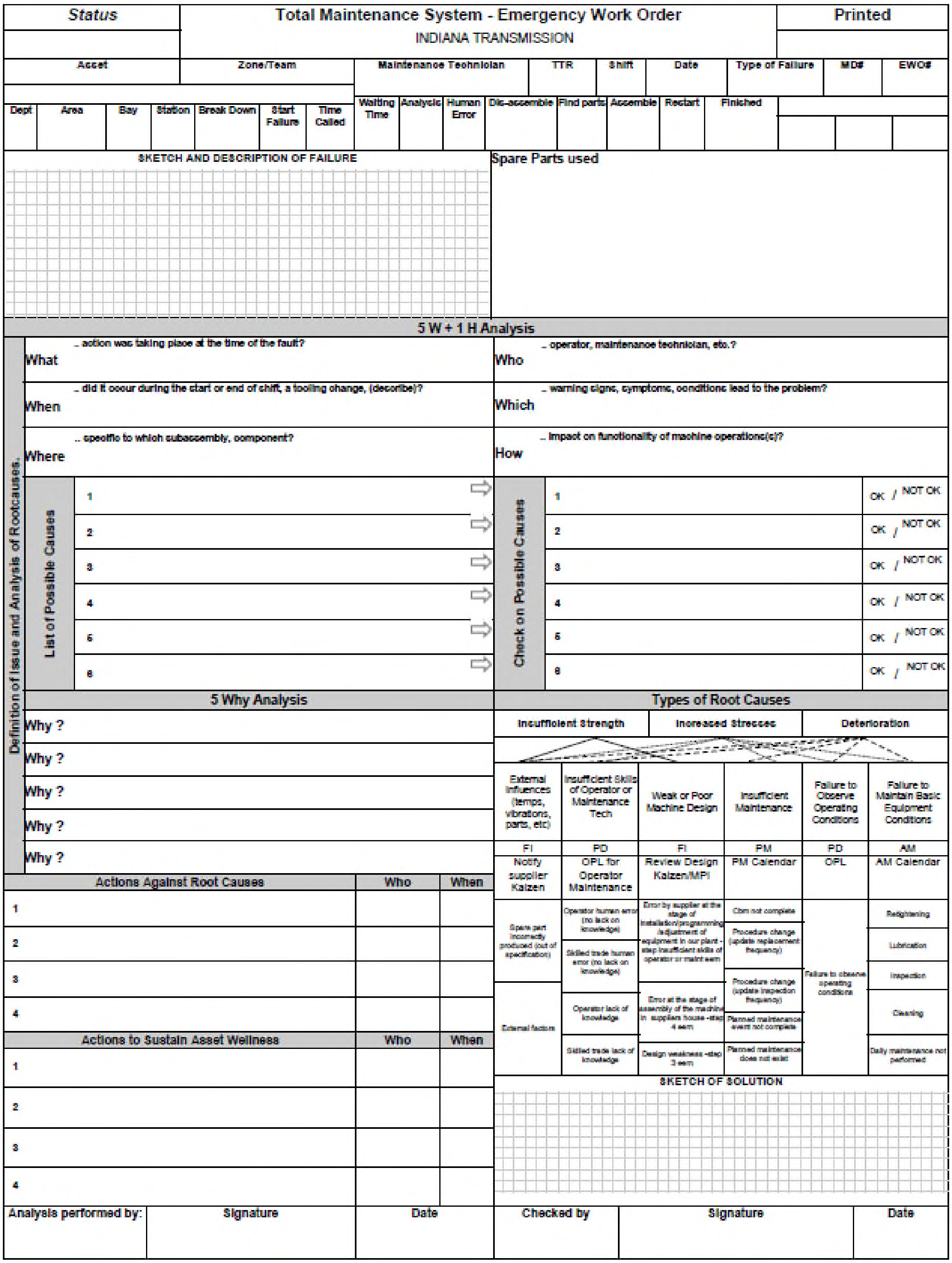
APPENDIX A

EMERGENCY WORK ORDER (WCM FIAT CHRYSLER, 2019)



Status

Total Maintenance System - Emergency Work Order

INDIANA TRANSMISSION

Printed

Asset	Zone/Team	Maintenance Technician	TTR	Shift	Date	Type of Failure	MD#	EWO#

Dept	Area	Bay	Station	Break Down	Start Failure	Time Called	Waiting Time	Analysis	Human Error	Dis-assemble	Find parts	Assemble	Restart	Finished

SKETCH AND DESCRIPTION OF FAILURE

Spare Parts used

5 W + 1 H Analysis

Definition of Issue and Analysis of Rootcauses

What .. action was taking place at the time of the fault?

Who .. operator, maintenance technician, etc.?

When .. did it occur during the start or end of shift, a tooling change, (describe)?

Which .. warning signs, symptoms, conditions lead to the problem?

Where .. specific to which subassembly, component?

How .. impact on functionality of machine operations(s)?

List of Possible Causes	Check on Possible Causes	
1	1	OK / NOT OK
2	2	OK / NOT OK
3	3	OK / NOT OK
4	4	OK / NOT OK
5	5	OK / NOT OK
6	6	OK / NOT OK

5 Why Analysis

Why ?

Why ?

Why ?

Why ?

Why ?

Types of Root Causes

Insufficient Strength | Increased Stresses | Deterioration

External Influences (temps, vibrations, parts, etc)	Insufficient Skills of Operator or Maintenance Tech	Weak or Poor Machine Design	Insufficient Maintenance	Failure to Observe Operating Conditions	Failure to Maintain Basic Equipment Conditions
FI	PD	FI	PM	PD	AM
Notify supplier Kaizen	OPL for Operator Maintenance	Review Design Kaizen/MPI	PM Calendar	OPL	AM Calendar
Spare part incorrectly produced (out of specification)	Operator human error (no lack on knowledge)	Error by supplier at the stage of installation/programming /adjustment of equipment in our plant - step insufficient skills of operator or maint eem	Clom not complete	Failure to observe operating conditions	Retightening
	Skilled trade human error (no lack on knowledge)		Procedure change (update replacement frequency)		Lubrication
			Procedure change (update inspection frequency)		Inspection
External factors	Operator lack of knowledge	Error at the stage of assembly of the machine in suppliers house -step 4 eem	Planned maintenance event not complete		Cleaning
	Skilled trade lack of knowledge	Design weakness -step 3 eem	Planned maintenance does not exist		Daily maintenance not performed

Actions Against Root Causes	Who	When
1		
2		
3		
4		

Actions to Sustain Asset Wellness	Who	When
1		
2		
3		
4		

SKETCH OF SOLUTION

Analysis performed by:	Signature	Date	Checked by	Signature	Date

APPENDIX B

FIGURE 3.2 MULTI AXIS LASER DATA SHEET

Machine Number: AAA20634	**Fuji CNC** **Z Axis Health Check**	**Date:** 11/15/18

Equipment- Automated Precision 6D- Axis Laser

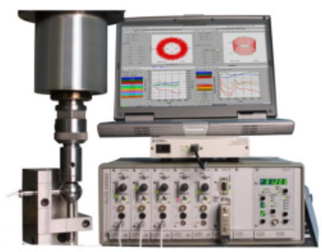
Feature Measured	Acceptance Specifications and Results			Measurement Method and Equipment Used
	Allowable Error	Actual Error	Deviation	
Linear Accuracy	0.040	0.003		EQUIPMENT REQUIRED: API LASER
Bi-Directional Repeatability	0.040	0.002		Z AXIS MEASUREMENTS WILL BE TAKEN AT 50 MM INTERVALS MACHINE DWELL 10 SEC
Reversal error	0.020	0.025	0.005	DATA WILL BE TAKEN OVER 3 BI-DIRECTIONAL RUNS.
Z Axis Straightness X Direction	0.045 Max Travel	0.030		
Z Axis Straightness Y Direction	0.045 Max Travel	0.060	0.015	Note: Gibs need to be adjusted, and Backlash needs compensated due to Pitch, Yaw and Reversal error out of tolerance
Z Axis Pitch (Angle YZ)	15 arcsec Max Travel	17.0	2.0	
Z Axis Yaw (Angle XZ)	15 arcsec Max Travel	16.0	1.0	
Z Axis Roll (Angle XY)	15 arcsec Max Travel	8.0		

Inspected By:	Date:	Control Compensation Used

APPENDIX C

FIGURE 3.3 SPINDLE ANALYZER DATA SHEET

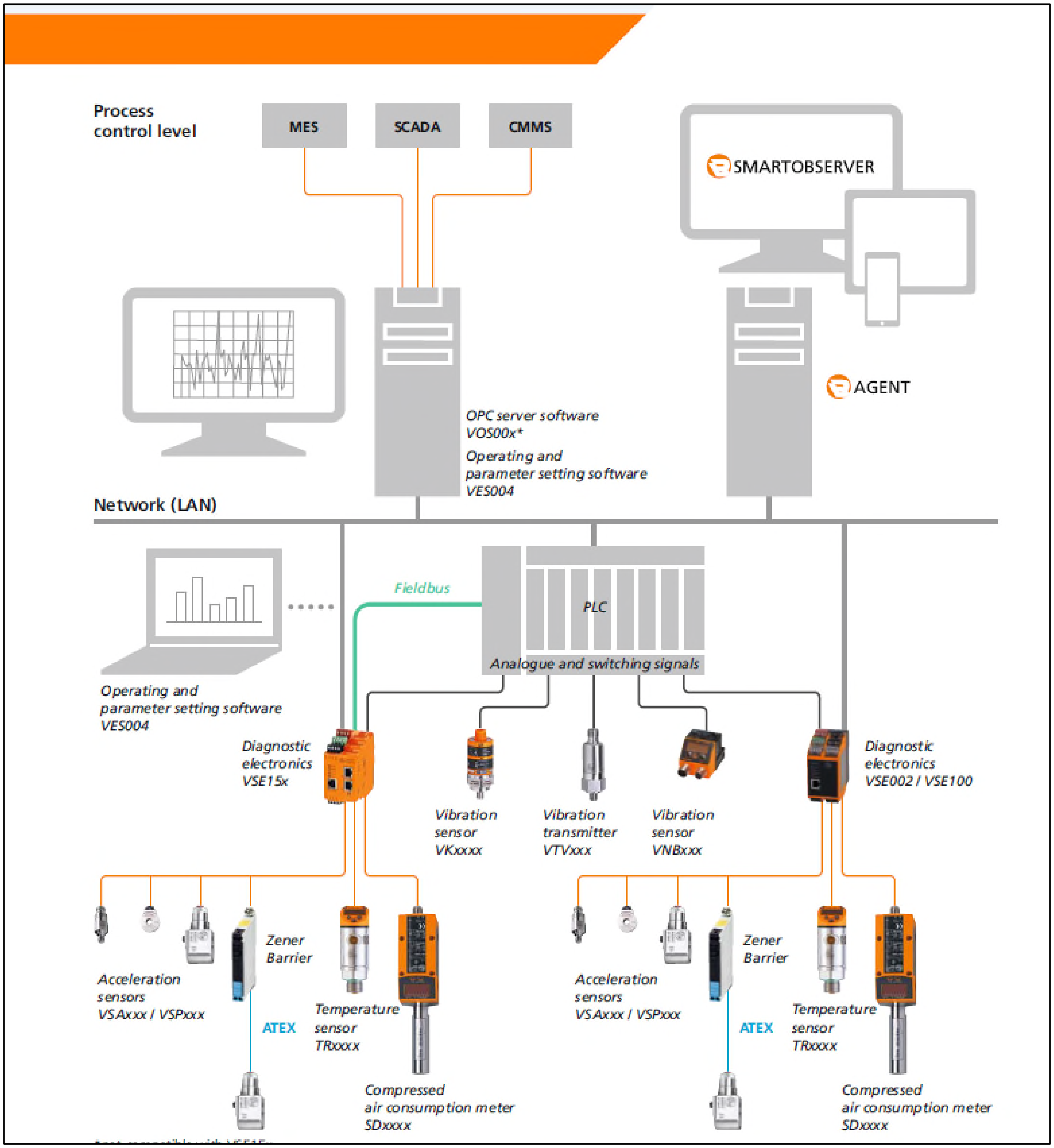
Machine Number AA479	Toyoda Spindle Unit			Date: 11/15/18
Spindle Analyzer Setup Illustration				



	Spindle Unit Radial Error			
RPM	Asyncronous Error Specifications and Results			Spindle and Measurement Description
	Allowable Error	Measured Error	Deviation	
400 (10% rated rpm)	0.0040	0.0030		SPINDLE DESCRIPTION: Max RPM 4000
2000 (50% rated rpm)	0.0060	0.0020		
4000 (100% rated rpm)	0.0080	0.0160	0.0080	
RPM	Average Error Specifications and Results			
	Allowable Error	Measured Error	Deviation	
400 (10% rated rpm)	0.0020	0.0010		EQUIPMENT REQUIRED: Lioins Dynamic Spindle Analyzer 19-20mm Collet
2000 (50% rated rpm)	0.0040	0.0030		
4000 (100% rated rpm)	0.0050	0.0030		
	Spindle Unit Axial Error			
RPM	Asyncronous Error Specifications and Results			
	Allowable Error	Measured Error	Deviation	
400 (10% rated rpm)	0.0040	0.0020		
2000 (50% rated rpm)	0.0060	0.0010		
4000 (100% rated rpm)	0.0080	0.0010		
RPM	Average Error Specifications and Results			
	Allowable Error	Measured Error	Deviation	
400 (10% rated rpm)	0.0020	0.0001		
2000 (50% rated rpm)	0.0040	0.0010		
4000 (100% rated rpm)	0.0050	0.0010		
Inspected By:			Date:11/15/18	
☐				

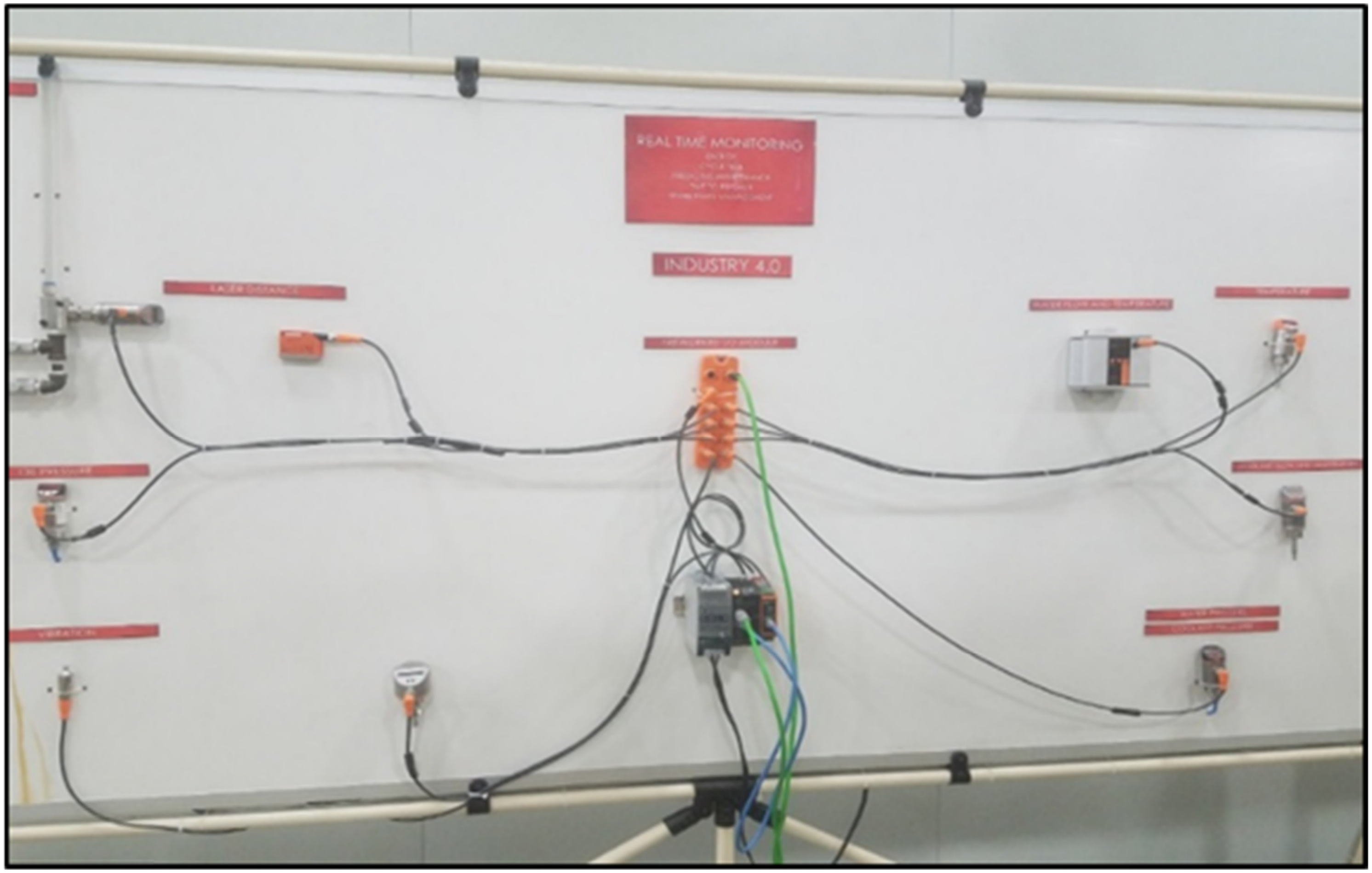
APPENDIX D

NETWORK AND PROCESS CONTROL (EFECTOR 2017)



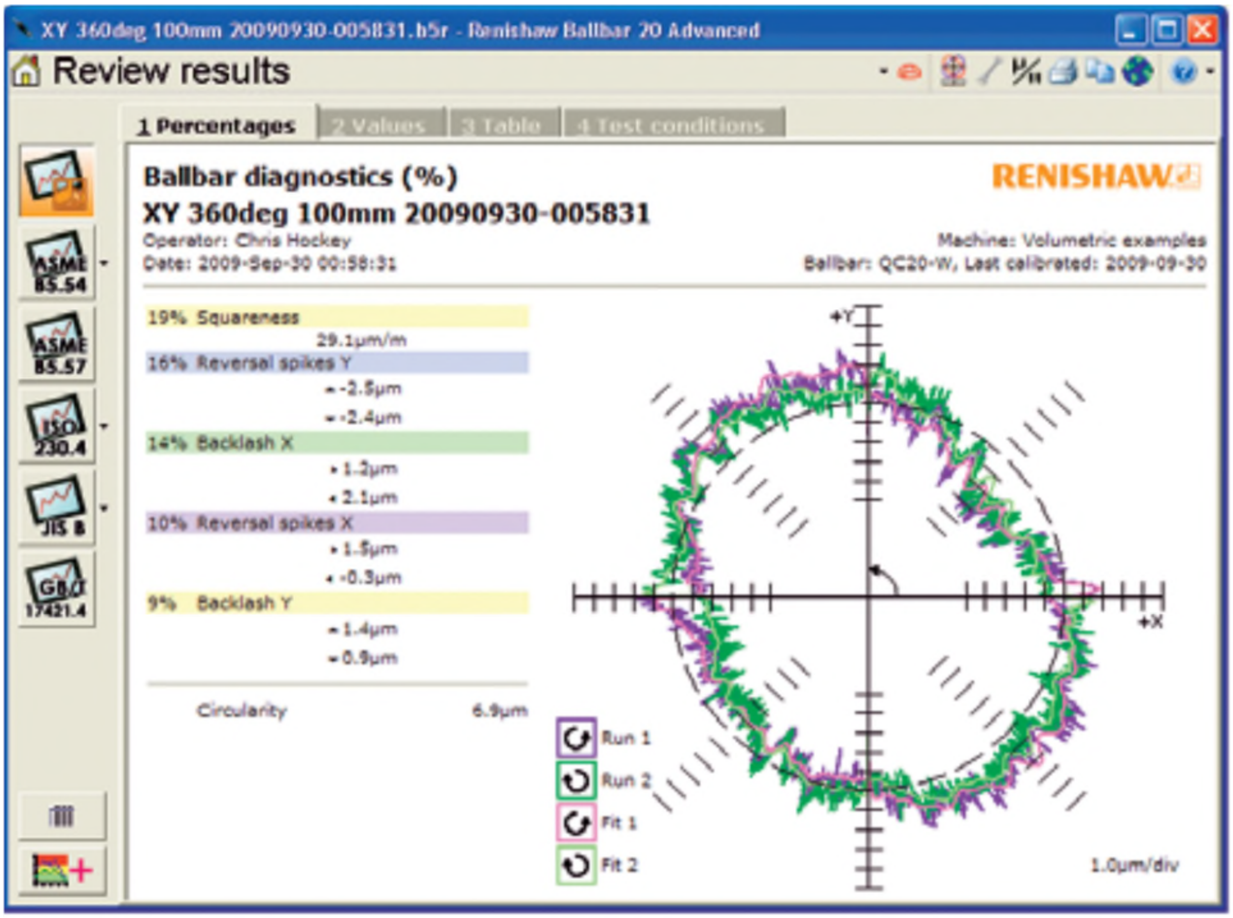
APPENDIX E

FIGURE 4.14 WHITE BOARD DISPLAY OF SMART SENSORS (FCA, 2019)



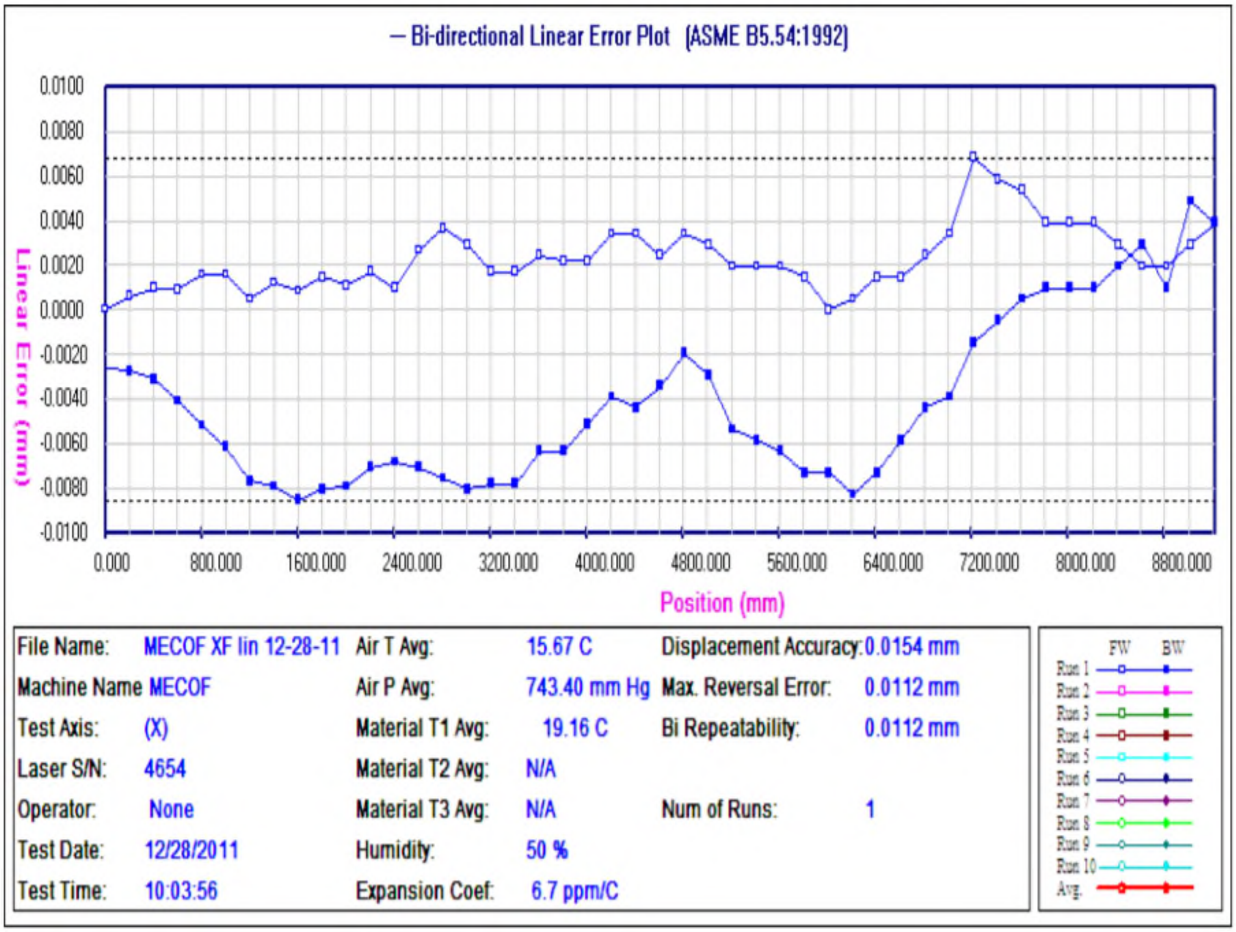
APPENDIX F

FIGURE 4.17 RENISHAW BALBAR DATA IMAGE (RENISHAW, 2013)



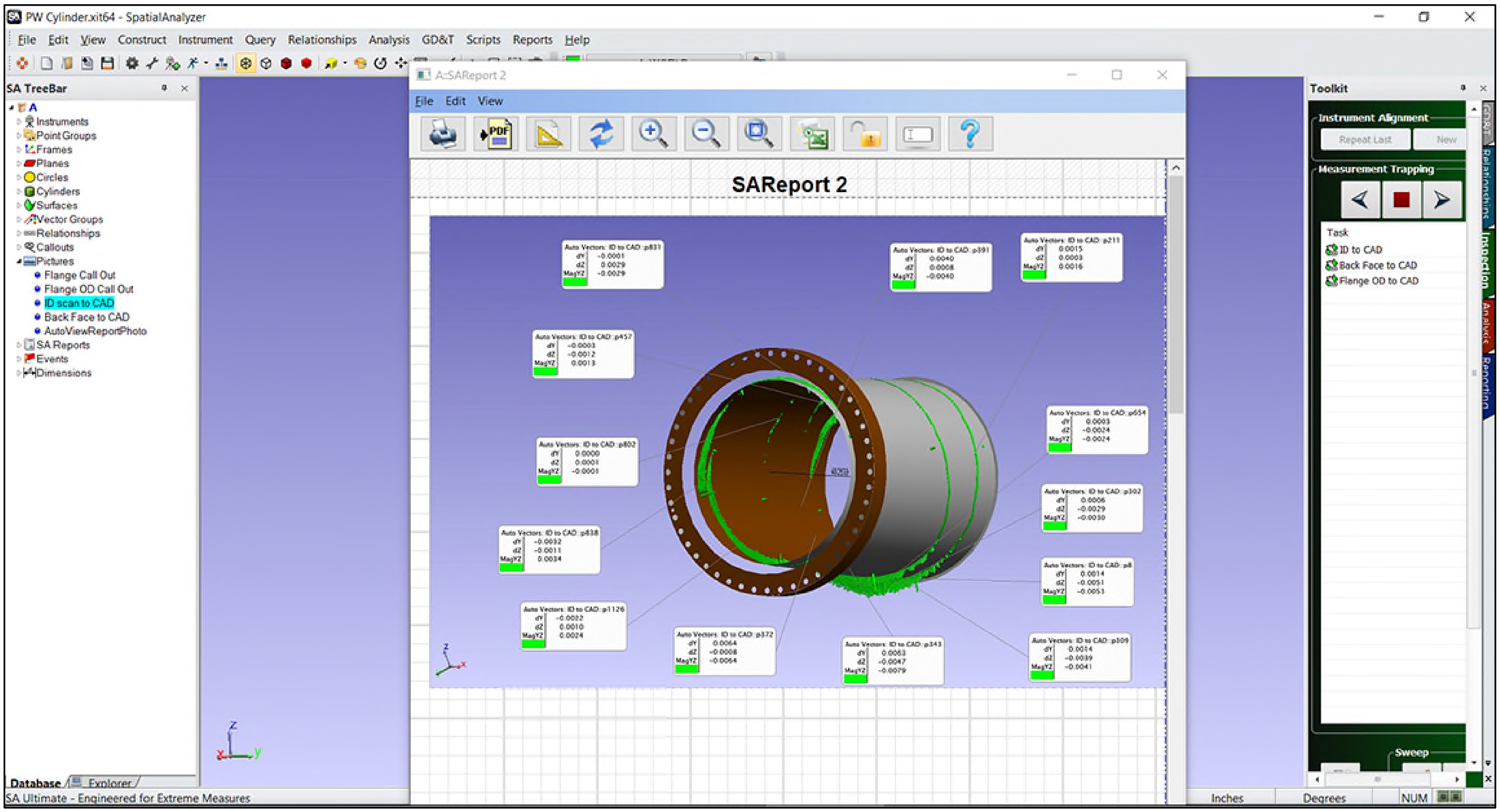
APPENDIX G

FIGURE 4.19 API RESULTS SCREEN SHOT (TOTAL MACHINE SERVICE N.D)



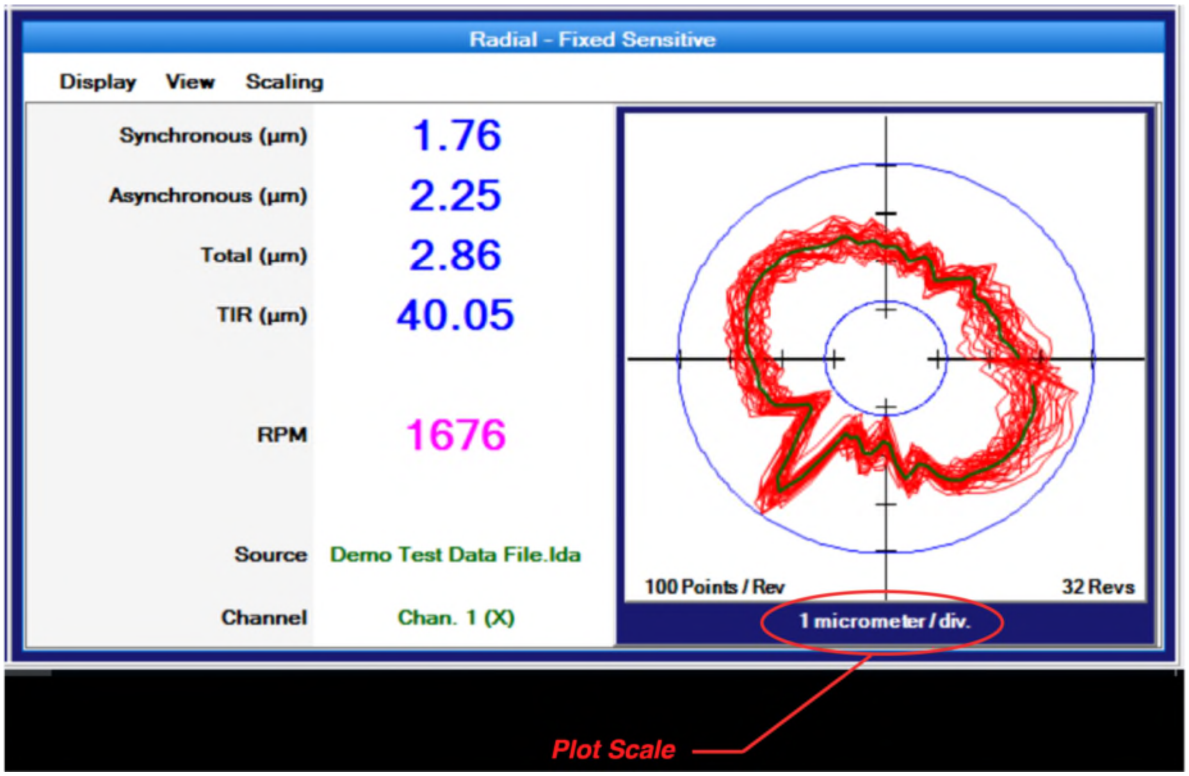
APPENDIX H

FIGURE 4.21 SPATIAL ANALYSIS REPORT (NEW RIVER KINEMATICS 2018)



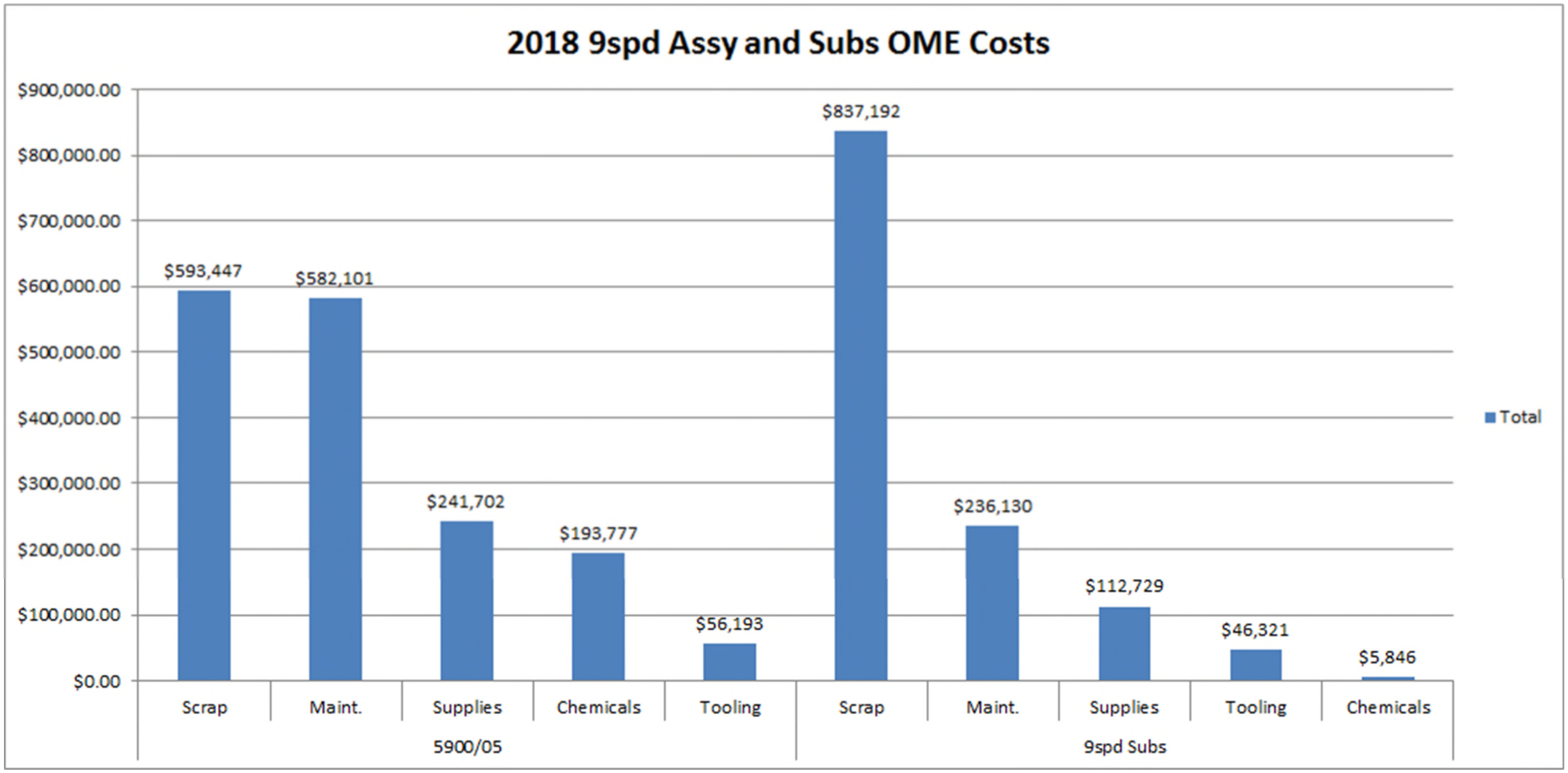
APPENDIX I

FIGURE 4.22 LION'S SEA SOFTWARE SCREEN SHOT (LIONS PRECISION, 2017)



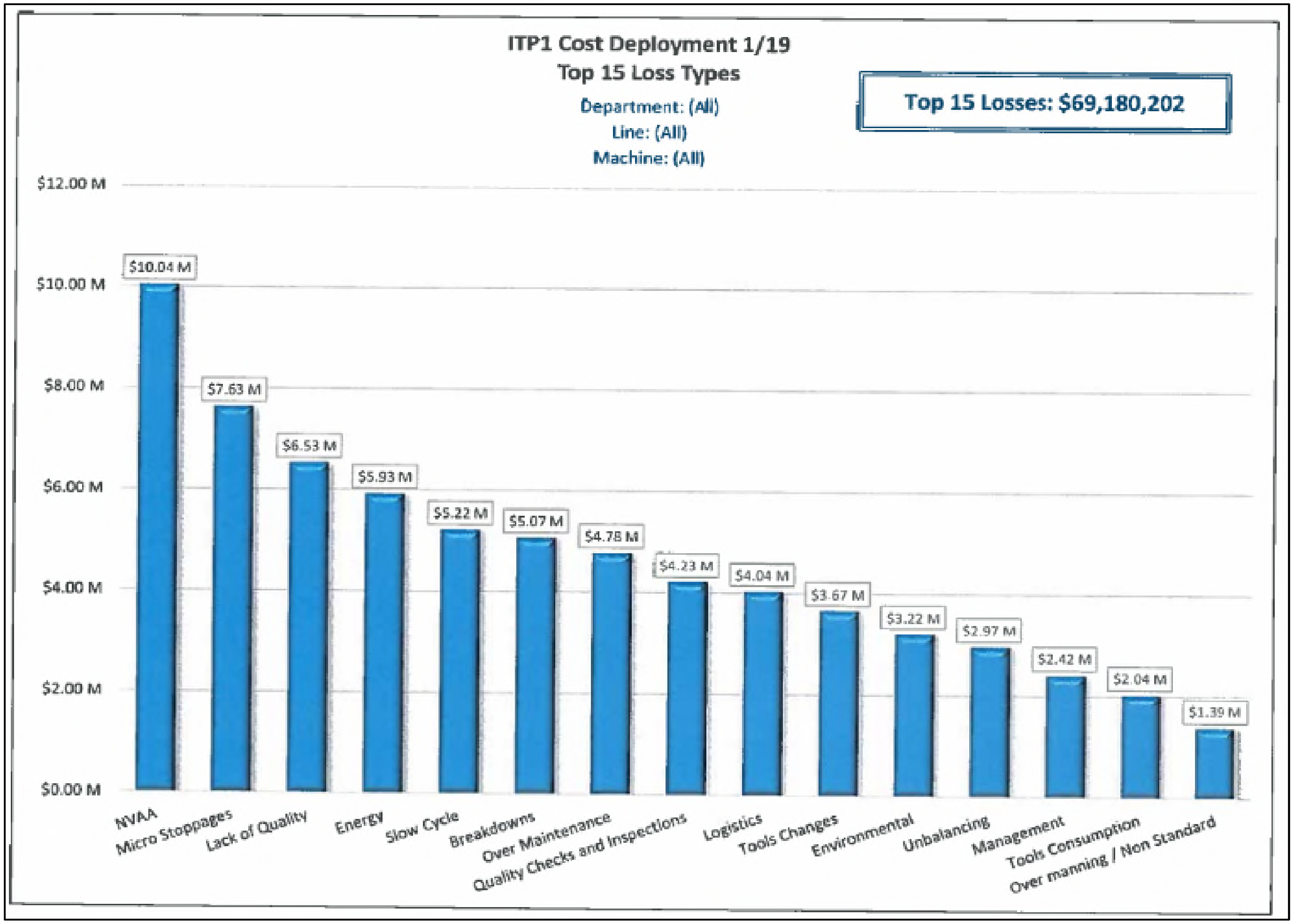
APPENDIX J

2018 OVERALL MACHINE EFFICIENCY COST (FCA, 2019)



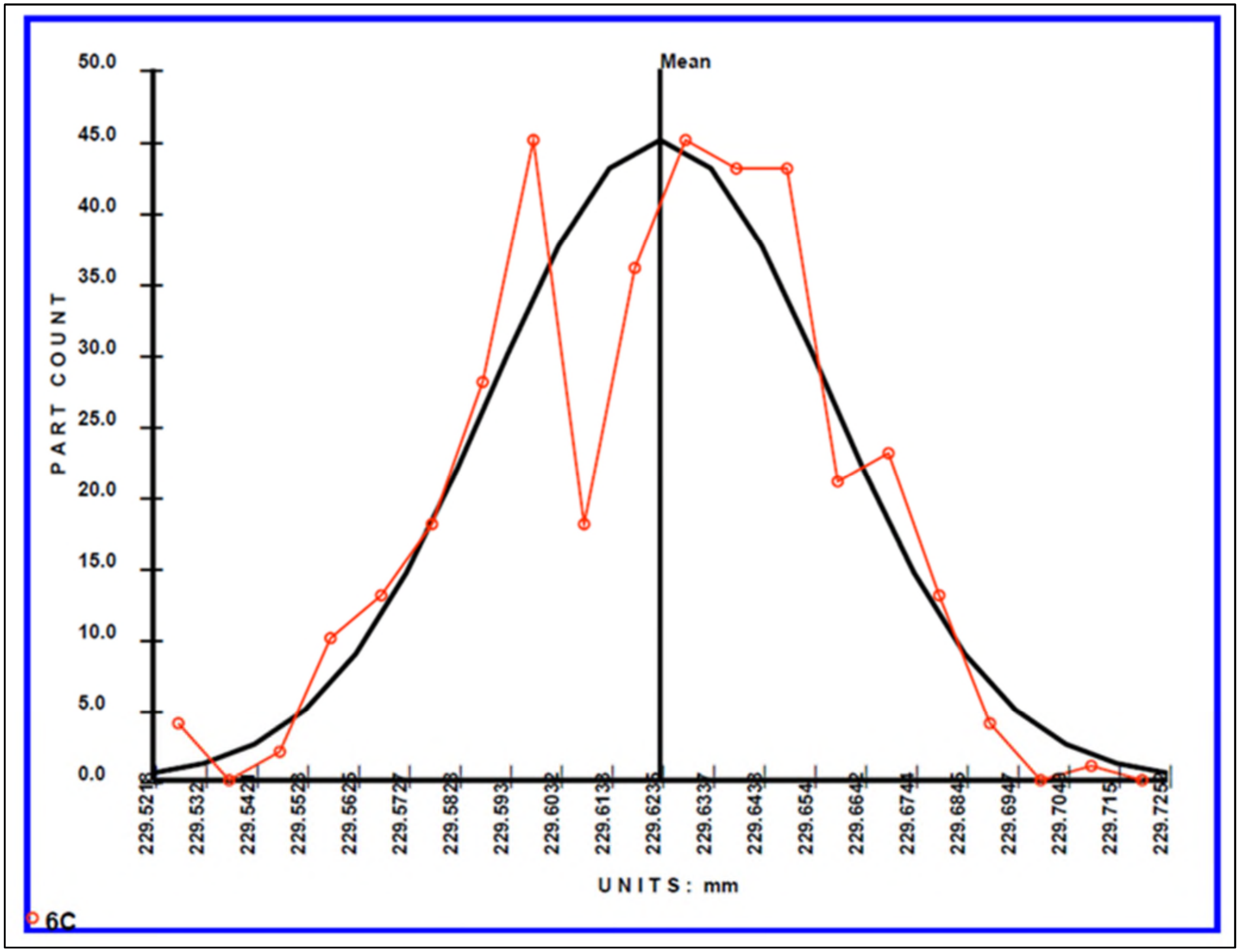
APPENDIX K

FIGURE 4.29 2018 PRODUCTION LOSS TIME CHART (FCA, 2019)



APPENDIX L

FIGURE 4.30 MANUFACTURING PARTS TRACKING SYSTEM QUALITY: HISTOGRAM (FCA, 2019)



APPENDIX M

FIGURE 4.31 2018 LOSSES BY DEPARTMENT DUE TO DOWNTIME (FCA, 2019)