Use Case Development to Advance Monitoring, Diagnostics, and Prognostics in Manufacturing Operations

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Abstract: Manufacturing operations suffer from degradation as equipment and processes are continually used to generate products. The development and integration of monitoring, diagnostic, and prognostic (collectively known as PHM) technologies can enhance maintenance and control strategies within manufacturing operations to improve asset availability, product quality, and overall productivity. As these technologies continue to evolve, it is critical for PHM technologies to be assessed to ensure the manufacturing community is aware of the true capabilities and potential of PHM technologies. The National Institute of Standards and Technology (NIST) has developed a use case that is representative of common manufacturing operations to support the assessment of PHM technologies. This use case will produce test scenarios, reference data sets and protocols, and verification and validation tools. The use case is described including its three constituent research areas: *Manufacturing Process and Equipment Monitoring*, *Machine Tool Linear Axes Diagnostics and Prognostics*, and *Health and Control Management of Robot Systems.*

Keywords: diagnostics, manufacturing processes, manufacturing systems, condition monitoring, prognostics, use cases

1. INTRODUCTION

Advanced technology continues to emerge and evolve leading to increasing capabilities within manufacturing operations. Smart Manufacturing or Industrie 4.0 are focused on integrating and connecting hardware, software, and data to increase operational efficiency, asset availability, and quality while decreasing unscheduled downtime and scrap (Kagermann et al., 2013) (McKinsey, 2012) (PCAST, 2012). This translates into manufacturing operations becoming more efficient to keep up with changing consumer demand and increasing competition.

Asset availability is critical for manufacturers to output products to meet consumer demand. Unexpected downtime and lost production are 'pain points' for manufacturers, especially in that they usually translate to financial losses. To minimize these pain points, the manufacturing stakeholder community (including manufacturers, technology developers, integrators, and academic researchers) are advancing monitoring, diagnostic, and prognostic (commonly known as prognostics and health management - PHM) technologies to improve maintenance and control strategies.

The United States (U.S.) Federal Government has a research focus in advancing the means of assessing, verifying, and validating PHM technologies operating within manufacturing environments (National Institute of Standards and Technology, 2016). This effort resides at the National Institute of Standards and Technology (NIST) and includes a focus on machine tool and robotic manufacturing operations. NIST researchers are actively developing use cases, performance metrics, test protocols and reference data sets to enable the verification and validation (V&V) of PHM technologies.

2. BACKGROUND

The need for PHM is motivated by the fact that as soon as you turn on a piece of equipment or initiate a process (requiring the interaction of one or more physical entities), the system begins to degrade, ultimately causing 'wear & tear.' If unchecked, this degradation will lead to faults or failures impacting the overall quality and/or productivity of the process. The field of PHM has emerged from the study, design, and implementation of monitoring, diagnostic, and/or prognostic technologies to minimize the occurrence of failures. PHM aims to increase our knowledge of a process so that one can make better maintenance and control decisions.

2.1 Manufacturing Health and Control Management

Four maintenance strategies have been documented and applied in varying extents across the manufacturing environment. The strategies are known as reactive, preventative, predictive, and proactive maintenance (Jin et al., 2016). Reactive maintenance is the simplest form of maintenance; no maintenance is performed on the machine until a failure occurs. Although this maintenance strategy is the easiest to implement (i.e., do nothing until something breaks), it is often the most expensive strategy when considering maintenance costs, lost asset availability, lost production, and potential collateral damage. Preventative maintenance is when maintenance is performed on specific unit intervals (e.g., x cycles, y hours) and is widely performed in the manufacturing industry (Ahmad and Kamaruddin, 2012) (Coats et al., 2011). Predictive maintenance, sometimes known as condition-based maintenance, uses health and/or performance data captured from the equipment or process to indicate when maintenance should be performed (Byington et al., 2002) (Tian et al., 2012). There are instances of manufacturers using predictive maintenance strategies within their operations, yet this is typically incorporated in areas where data collection, and subsequent analysis, is feasible and there is a known value proposition to such a strategy. Proactive maintenance, sometimes known as intelligent maintenance, is an emerging strategy that relies upon data collection from the manufacturing process to improve and sustain the process, in addition to minimizing the occurrence of failures (Barajas and Srinivasa, 2008) (Lee et al., 2011) (Lee et al., 2006). Proactive maintenance is unique from other maintenance strategies in that it is marked by varying levels of equipment or process intelligence in terms of maintenance and control activities. Equipment or processes have some capability(ies) in performing certain maintenance activities until an appropriate human intervention can be achieved or until specific production objectives are met. Proactive maintenance is the most advanced of the maintenance strategies and is minimally employed given its state of development. Aside from implementing reactive maintenance, the implementation of preventative, predictive, and/or proactive maintenance will lead to improved health and control management of a piece of equipment or an overall process.

Apart from reactive maintenance, these maintenance strategies are each supported by monitoring, diagnostics, and prognostics (to a certain extent). Monitoring is the act of identifying, observing, or understanding the current health state of equipment or a process. Diagnostics is the determination of what is going to fail and, depending upon the system, where the failure will occur. Prognostics is the determination of the future state of the equipment or process. Prognostics is also responsible for predicting the remaining useful life (RUL) of equipment or a process (Ly et al., 2009).

The advancement of monitoring, diagnostic, and prognostic technologies has increased the development and implementation of preventative, predictive, and proactive maintenance strategies. A wide range of techniques, algorithms, and practices have been developed with varying success (Vogl et al., 2016b). Not only has PHM enhanced maintenance strategies, but it has also promoted more intelligent control of processes. Some monitoring, diagnostic, and prognostic techniques feed adaptive control strategies allowing processes to automatically adjust their performance (or output) given their current state of health (Ehrmann and Herder, 2013, Liu, 2001) (Shin and Lee, 1999). These control strategies are limited and have room for expansion.

2.2 Manufacturing Case Studies

According to the manufacturing and PHM communities, there is still much work to be done to improve monitoring, diagnostic, and prognostic practices to enhance maintenance and control strategies. NIST personnel conducted manufacturing case studies to understand the current successes and challenges to developing and implementing PHM within manufacturing operations. This information was gathered by having representatives of the manufacturing community come to NIST or by NIST personnel directly reaching out to manufacturers via phone calls or site visits.

A workshop was held at NIST that brought together small, medium, and large-sized manufacturers along with technology developers, technology integrators, academia, government, and standards development organizations to examine the challenges and barriers to advancing the state of PHM within manufacturing operations. This workshop resulted in the generation of a substantial roadmapping document that highlighted over a dozen research topics that should be undertaken to enhance the state of PHM (National Institute of Standards and Technology, 2015). The workshop presented some trends across multiple manufacturers as far as areas for improvement. Some of the common themes included the manufacturing community’s desire to 1) better understand and integrate advanced sensing capabilities into equipment and processes to increase PHM, 2) identify a suite of common PHM performance metrics that would present a holistic understanding of equipment or process health, and 3) generate/access larger volumes of structured and contextualized failure data for prognostics and diagnostics to promote further maintenance strategy development (Weiss et al., 2015).

NIST personnel, and their collaborators from the University of Cincinnati and the University of Michigan – Ann Arbor, spoke/met with over 30 manufacturers representing small to medium-sized enterprises (SMEs) and large companies (Helu and Weiss, 2016) (Jin et al., 2016). Many trends, including similarities and differences, were documented between SMEs and large companies. One similarity that stands out is that no single organization used the same maintenance strategy across all of its equipment and processes. For example, some companies employed a mix of reactive and preventative maintenance strategies, while other companies employed a mix of preventative and predictive maintenance with minimal reactive maintenance. One of the biggest differences between SMEs and large companies is that an overwhelming majority of the large companies are more advanced in their maintenance strategies as compared to the SMEs. This can be attributed to the greater resources available to the large companies including more financial capital and available personnel. These manufacturing case studies also revealed some common scenarios in which implementing or increasing PHM would be beneficial to a process’ asset availability, output quality, and overall productivity.

3. USE CASE DEVELOPMENT

It is imperative to generate appropriate use cases to produce test scenarios, reference datasets and protocols, and V&V tools that allow technology developers and integrators to address the manufacturing community’s needs and promote the evaluation of various technology options. Six areas for theoretically impactful use cases emerged from the case studies:

- Planning and scheduling support
- Maintenance planning and spare part provisions
- Request for proposals
- Resource budgeting (e.g., capital investments)
- Workforce augmentation
- Automation

NIST personnel identified an initial use case that would feature several of the six areas mentioned above, represent a manufacturing operation common in numerous organizations, and also present numerous individual elements prevalent within many manufacturing environments. This case study (depicted in Fig. 1) presents a production work cell containing representative systems common in modern manufacturing facilities, including computer numeric control (CNC) machine tools and a six-degree-of-freedom (6-DOF) industrial robot arm. The concept of operations is that materials and resources are input into the cell and are dynamically routed to one or more machines based upon the current and predicted status of the machine tools, their components, and the robot manipulating the parts. The use case features the robot performing machine tending by first presenting a machine tool with a part to be machined and then removing the part from the machine tool once the machining operations have been completed. These elements would be coordinated with each other based on the quantified state of all components by a principal control system. This control system would route materials dynamically based on the measured state and performance of the system as well as input from design, engineering, suppliers, and other actors across the manufacturing enterprise (Helu and Weiss, 2016).

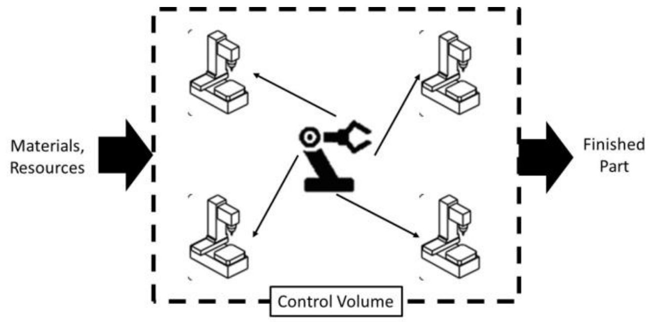

Fig. 1. NIST Use Case Production Cell

Other use cases are being considered, including 1) multiple 6-DOF industrial robot arms assembling parts after the parts have been machined by one or more machine tools and 2) a 6-DOF industrial robot arm moving machined parts from a conveyor to a fixture so that another 6-DOF industrial robot arm may 'mark' the fixture part. Each of these use cases, including the initial use case, are being carefully chosen to represent a majority of the machine tool and robot system scenarios that were encountered during the case studies and documented during the NIST workshop.

The initial use case is designed such that it is relevant to industry, allows for the practical implementation of NIST's research efforts, and can be supported by NIST's test beds. Use case implementation has begun with several of NIST's research efforts. Specifically, these efforts (presented in sections 4 and 5) highlight key elements that will ultimately be integrated together via the use case.

4. USE CASE IMPLEMENTATION

The initial use case described in Section 3. is currently broken down into three key research elements: *Manufacturing Process and Equipment Monitoring*, *Machine Tool Linear Axes Diagnostics and Prognostics*, and *Health and Control Management of Robot Systems*.

4.1 Manufacturing Process and Equipment Monitoring

The *Manufacturing Process and Equipment Monitoring* research effort is aimed at monitoring the overall health of a manufacturing shop floor including the health of resident machine tools. This effort is driven by the need to identify high-value data sources and the most appropriate opportunities to collect data to avoid the challenges of big data. The focus is on having the right data at the right time to improve decision-making with respect to process and equipment performance. This research is supported by the development of a systems-level test bed of networked machine tools and sensors in an active manufacturing facility (Helu and Hedberg, 2015). The test bed provides a valuable testing and prototyping environment replete with rich data to support fundamental research, technology, and standards development. This research area will focus on integrating heterogeneous shop-floor systems through the development and advancement of standards and protocols. Specifically, the task will integrate sensors (including accelerometers, cameras, and thermocouples), machine tool controllers, and production management systems. Initial standards research focuses on the extension of MTConnect across manufacturing equipment and systems.

This research encompasses a substantial portion of the initial use case. The test bed includes a heterogeneous mix of machine tools with different capabilities and operating on varying controllers, that must effectively function in the same environment to meet the shop's overall production schedule. The defined use case includes multiple machine tools that will be called upon to perform a range of operations to fabricate specific parts. Until the robotics portion of the use case is integrated, parts will be placed and removed within the machine tools by human operators.

The test bed is currently online and streaming publicly available data from several machine tools that are in regular use by NIST Fabrication Technology machine shop personnel (Hedberg and Helu, 2016). The online data stream is provided using data formats defined in the MTConnect standard. Additional sensors are integrated with many of the machine tools to capture more data that can provide greater clarity on individual machine and overall process health. One such sensor that is being integrated with the test bed, and therefore the use case, is that of a novel sensor fusion device that generates error data of machine tool linear axes.

4.2 Machine Tool Linear Axes Diagnostics and Prognostics

Most information that is viewed at the shop-floor level originates from a lower level. These lower levels include the process, equipment, and component levels. Focusing on machine tools, there are numerous components that are prone to faults and failures throughout a machine tool's life that should be monitored to minimize unplanned downtime. Axis degradation is a reality of machine tools; monitoring axis health can also promote greater asset availability. Accurately detecting degradation of linear axes is typically a manual and time-consuming process. While direct methods for machine tool performance evaluation are well-established (International Organization for Standardization, 2012) and reliable for position-dependent error quantification, such measurements typically interrupt production (Khan and Chen, 2009). One potential solution for online monitoring of linear axis degradation is the use of an inertial measurement unit (IMU) (Vogl et al., 2015).

As seen in the schematic (Fig. 2), an IMU is mounted to a moving machine tool component. To diagnose axis degradation, the axis is moved back and forth at various speeds to capture data for different frequency bandwidths. This data is then 'fused' to estimate the changes in the 6-DOF geometric errors of the axis. Ideally, data would be collected periodically to track axis degradation with minimal disruptions to production. With robust diagnostics and prognostics algorithms, incipient faults may be detected and future failures may be avoided. This research supports the use case by offering another component-level sensor suite and methodology to monitor machine tool health. Prior to integrating this novel IMU into the larger shop floor test bed and the use case, it is critical that the methodology go through initial testing, independently of any machine tools.

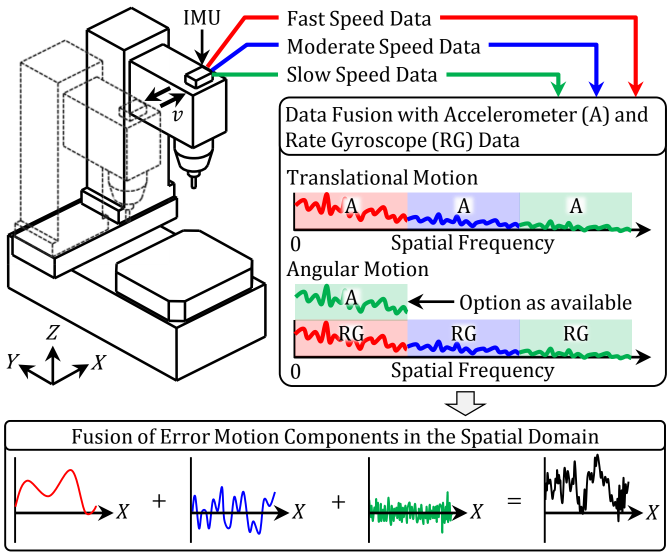

Fig. 2. IMU-based method for diagnostics of machine tool performance degradation.

A test bed was designed for evaluation of the IMU-based method. As seen in Fig. 3, the test bed includes a translation stage, the IMU, a commercial laser-based system for measuring the geometric errors of the axis, and a direct current (DC) motor with encoder for motion control. While the metrology system measures the motion of the carriage with respect to the base of the linear axis, the carriage-mounted IMU measures the changes in the inertial motion of the carriage. The metrology system measures straightness and angular error motions over the travel length of 0.32 m with standard uncertainties of 0.7 μm and 3.0 μrad. The laser-based system is used for verification and validation (V&V) of the IMU-based results.

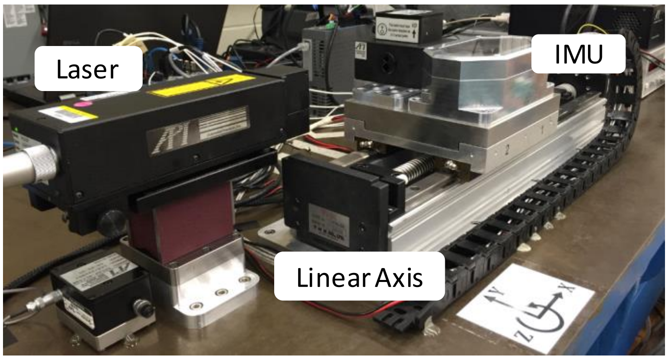

Fig. 3. Linear axis testbed

The IMU-based method relies on fusion of data collected at three programmed speeds of the carriage. The different speeds allow for sensing of repeatable error motions, composed of low to high spatial frequencies, within different temporal bandwidths. (Vogl et al., 2016a). Each 'run' is composed of data collected at the three axis speeds, and the resulting error motions per run are averaged to produce the final IMU-based error motions.

Typical laser-based and IMU-based results averaged for 50 runs are compared against one another to evaluate the methodology. The standard deviations of the differences are 11 μm, 2.3 μm, and 13 μrad for the linear positioning, straightness, and angular error motions, respectively. Due to the smallness of the deviations, the IMU-based method may be used for the estimation of changes in geometric motion errors of linear axes. Consequently, IMU data can be used to help optimize maintenance of machine tools for improved production planning and ultimately part quality.

4.3 Health and Control Management of Robot Systems

Similar to a machine tool, a robot system will begin to degrade from the moment it is put into operation. Although a 6-DOF industrial robot arm may be relatively robust, the robot system is a different story, altogether. The robot system includes the arm, end-effector, sensors, controller(s), safety systems, supporting automation, and human machine interface (HMI). Not only is each one of these elements susceptible to certain failures, the integration of these components and formation of specific relationships can increase the pace of degradation and lead to a cascade of failures.

The robot system is a key element of the initial use case defined in Section 3. To successfully accomplish its machine tending operations within the use case, the robot system must be aware of each machine tool's status that it intends to interact, aware of its own status (e.g., its current health and position), and aware of its environment (e.g., presence of an operator in its work volume). Without monitoring, diagnostics, and prognostics, a robot system will effectively function for a limited amount of time before it is likely to experience a fault or failure.

A robot systems test bed is under construction to support a framework for the assessment of monitoring, diagnostic, prognostic, and control technologies. The test bed will serve as the home to several industrial robot arm systems and will promote the generation of test methods and datasets. Advanced sensing and data collection techniques (what information to collect, how to collect, sensors to use, etc.) will be developed. Reference datasets will be generated to offer researchers and manufacturers a means of verifying and validating their diagnostic and prognostic techniques without the need for their own physical implementations. Reference data processing algorithms (data synchronization, data fusion of multiple sensor streams, and PHM data formats for interoperability) will be developed to analyze the PHM data that assesses the robot system's health metrics. This will support the closed-loop framework with the inclusion of diagnostic and prognostic techniques to promote better decision making for updating maintenance and control strategies.

5. FUTURE WORK

Each of the three research areas presented in Section 4. are in various phases of development and will ultimately be integrated together to form the defined use case. Efforts are under way to increase the data output from the Smart Manufacturing Systems Test Bed from two machine tools to approximately ten within the *Manufacturing Process and Equipment Monitoring* research. This will increase the publicly available volatile data stream and offer greater data sets to further support use case development. Besides getting additional machine tools online, more sensors are being planned for integration. Near term additions include power meters and the IMU sensor box presented in Section 4.2. The IMU sensor box design has been further refined from its original design to present a smaller profile when mounted to the axes of a machine tool. It is expected that the IMU sensor box will be mounted to a NIST machine tool in late 2016 so that it will capture linear axes error data during a pre-defined start-up sequence (at minimum) and during cutting operations (ideally). This data will be compared against machine tool controller data, including planned and actual data from the controller.

The *Health and Control Management of Robot Systems* effort will continue to evolve. To support the initial use case, a quick health assessment methodology is being developed to identify the health of the robot system, with an emphasis on a subset of the robot health performance metrics – tool center point accuracy and accuracy of tool center velocity. This effort will allow manufacturers to quickly assess the positional health of their robot systems when environmental conditions change, or after a work cell has been reconfigured. In turn, this methodology can also enable manufacturers and technology developers to verify and validate their own PHM techniques that monitor robot health in terms of static and dynamic accuracy. Further evolution of this effort will continue in the form of adding more sensors to monitor robot health, position, and environmental conditions/parameters. Likewise, the complexity of the robot system will be increased with the inclusion of an end-effector and supporting automation (e.g., conveyor belts to present parts to the robot arm).

6. CONCLUSION

An initial use case is documented that originates from feedback received from SME and large manufacturers. This use case provides an opportune breeding ground to develop test methods, reference data sets and protocols, and V&V tools to promote the assessment of monitoring, diagnostic, and prognostic techniques. These PHM techniques have been identified by the manufacturing community as necessary research areas to advance and promote more intelligent maintenance and control strategies. NIST is contributing to the overall PHM research field in the development of this use case to include three key research areas: *Manufacturing Process and Equipment Monitoring*, *Machine Tool Linear Axes Diagnostics and Prognostics*, and *Health and Control Management of Robot Systems.* Individually, and together, each of these research areas represents common operations whose degradation and overall health need to be understood to promote sustained, efficient manufacturing.

NIST DISCLAIMER

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