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ROBOTIC WORK CELL TEST BED TO SUPPORT MEASUREMENT SCIENCE FOR MONITORING, DIAGNOSTICS, AND PROGNOSTICS

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ABSTRACT

Industrial robotics users, integrators, and manufacturers are implementing advanced monitoring, diagnostics, and prognostics (collectively known as Prognostics and Health Management (PHM)) techniques and technologies. PHM can take many different forms when implemented, and measures of effectiveness are highly dependent on the techniques implemented. A test bed has been built, and a use case designed, to represent common manufacturing tasks performed in robot work cells where PHM can provide greater equipment and process health intelligence. The physical and functional relationships within the work cell are mapped using a hierarchical deconstruction method to gain a better understanding of the propagation of effects of both equipment and process degradation. The test bed has been built so PHM techniques and technologies can be integrated and tested in a realistic scenario. Data is recorded for post processing and analysis for the verification and validation (V&V) of the implemented PHM techniques. The test bed will serve as a platform to develop, test, verify, and validate PHM techniques at the National Institute of Standards and Technology (NIST), and provide industry participants a standard platform for testing their PHM technologies. Having a common testing platform will provide industry a foundation for sets of tests to evaluate PHM. This paper presents the test bed and use case, the relationships therein, and the data management and collection approaches used to enable future research.

INTRODUCTION

Once a robot system is implemented in a manufacturing environment, it must maintain a level of health to meet its necessary performance targets [1-3]. As with most automation technologies, robot system effectiveness is measured using metrics tailored to the process that is being performed [4, 5]. Different metrics are used by the manufacturing community to increase awareness of a robot system's health state and the operation(s) it performs. Most metrics present current and/or historical information. If any predictive performance metrics are used, they often do not consider future health degradations of system components [6-9].

The manufacturing community is motivated to monitor the degradation and predict the future health states of their robot systems to prevent faults and failures which ultimately impact performance [10, 11]. Advanced monitoring, diagnostics, and prognostics (collectively known as Prognostics and Health Management (PHM)) is an active area of research to support robot manufacturers, integrators, and users [7, 12-15]. There is a need to develop techniques to verify and validate (V&V) PHM technologies for robotics within manufacturing operations.

Across the manufacturing robot systems community, there is no uniform way to implement PHM. Similarly, there is no standard means of performing V&V of PHM methods as applied to robot systems. Standards do exist for some PHM methods, yet they are often specific to a piece of equipment (i.e., machine tool monitoring and diagnostics) or an application within the robotics community [12, 16-18]. The lack of broad PHM standards for industrial robot systems is in part due to the inherent complexity of robot systems and their wide use across many applications with supporting automation and peripheral equipment. There are many complex elements that interact with one another to form an industrial robot. To integrate a robot into a system adds more complexity, physical interactions, and functional relationships that influence system health. PHM can also be applied at multiple levels within a system. Examples of the various levels where PHM can be applied within a manufacturing process include components (e.g., actuators, robots), work cells, assembly lines, and factories [2, 6, 19].

The National Institute of Standards and Technology (NIST) is conducting research to develop the necessary means to V&V PHM technologies. A part of this research is focused on PHM for an industrial robot work cell. A robot work cell is defined as a system, including robot(s), controller(s), safety equipment, and other peripherals [20]. Parts typically flow into a work cell where they are manipulated and/or transformed before leaving the work cell. Common types of industrial robot work cells include material handling (e.g., machine tending, sortation), dispensing (e.g., adhesive dispensing), and assembly (e.g., welding).

There is no widely-accepted metric that assesses the health of a robot work cell. However, overall equipment effectiveness (OEE) is a commonly-used metric that can provide some insight on the value of maintaining work cell health. OEE is derived from three critical metrics: quality, performance (or productivity), and availability [21, 22]. All manufacturers seek to maximize their OEE. Because of this, OEE is used as a starting point in selecting what data is collected in the test bed to ensure that PHM methods being verified detect degradations which impact the metrics and measures that contribute to OEE. System health can either increase OEE (under healthy conditions) or decrease OEE (under degraded conditions). Quality of part output is related to robot position accuracy in work cells where the relationship between a part and tool is critical to the operation being performed. This is visible in operations such as dispensing, welding, and deburring. In this case, the robot's end effector is the tool and works directly on the part or the part is moved by a robot around a static tool. Performance is tied to the operational speed of components within a work cell including robot joints, conveyors, other moving parts, and the signals that control event-based movement [23, 24]. A reduction in speed has a clear impact on material handling tasks where the timing of movements is critical to maintain throughput. Availability is directly related to the health of a robot work cell. A robot that is not available is either not healthy or the robot is adversely impacted by a relationship it may have with an unhealthy element. Ideally, implementing PHM will maximize availability of a system by minimizing unplanned downtime and reducing planned downtime [25, 26].

The health of a robot work cell is dictated by the health of the components that comprise the work cell. In most work cells, there are complex relationships and interactions between components. These relationships and interactions can influence process time and quality. Part production can be influenced by almost any component of the system and generally requires every component to perform as intended to yield parts within specification. Mechanical components must be dimensionally accurate, parts must be within design tolerance, sensors must operate properly, sensor signals must be interpreted properly, and the algorithms (programming) that processes information must operate as designed. With the possibility of any component degrading, the relationships between the components must be understood.

This paper presents a test bed designed and constructed at NIST to serve as a platform to develop, test, and V&V PHM techniques and technologies. The following (second) section presents the test bed configuration and use case. The third section briefly discusses a hierarchical decomposition methodology and its preliminary application to the use case. The fourth section introduces the data management and collection approach to capture performance, process, and quality data. The fifth section presents sample data captured from the test bed. The final section concludes the paper and highlights next steps in this NIST research effort.

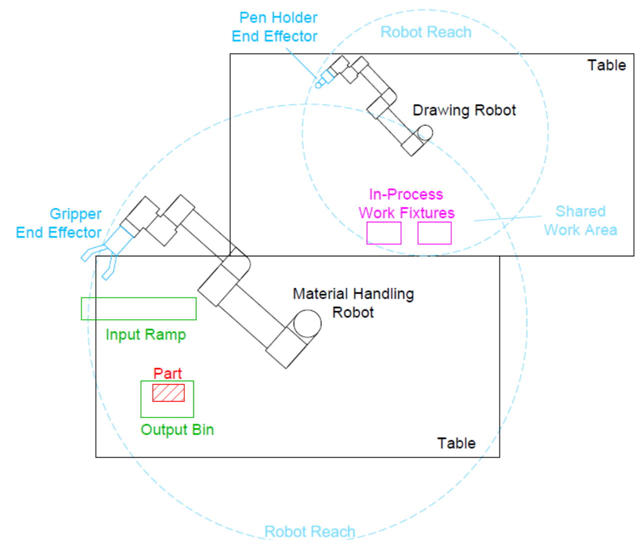

FIGURE 1. LAYOUT OF THE PHM TEST BED

TEST BED CONFIGURATION AND USE CASE

A test bed has been built to develop, test, verify, and validate PHM methods [27]. The test bed is configured to perform a process comprised of tasks that are similar to those found in common industrial robot applications. while making data (sensor data, robot data, etc.) available for PHM method V&V. The test bed is capable of real-time monitoring and control, and recording data for post processing and analysis. The test bed includes two industrial robots, end effectors for each robot, parts, and fixtures integrated to form a work cell (Fig. 1). The use case is a work cell that performs the following actions: receives parts, moves parts to a position to be drawn on, draws on the parts, then moves the parts to an output to be removed from the work cell. There is a single input location and a single output location. There are two available work fixtures where parts can be drawn on.

The use case process can be decomposed into three main tasks that are performed by the two industrial robots in the following order (per part): 1) the material handling robot performs a pick and place operation, moving a raw part from the input to a work fixture; 2) the drawing robot draws on the part, transforming the raw part into a completed part; 3) the material handling robot performs a pick and place operation, moving a completed part from a work fixture to the output (Fig. 2). A gravity-driven ramp inputs parts within reach of the material handling robot; the output consists of a box that parts can be dropped into where they are considered removed from the work cell. Once a part is placed on a work fixture by the material handling robot, the part is held in place by locating pins integral to the fixture. These pins mate with cylindrical locating holes on the bottom of the parts (Fig. 3). The locating pins have tapered ends to allow the part to self-center when there is a slight misalignment between part and fixture during part placement.

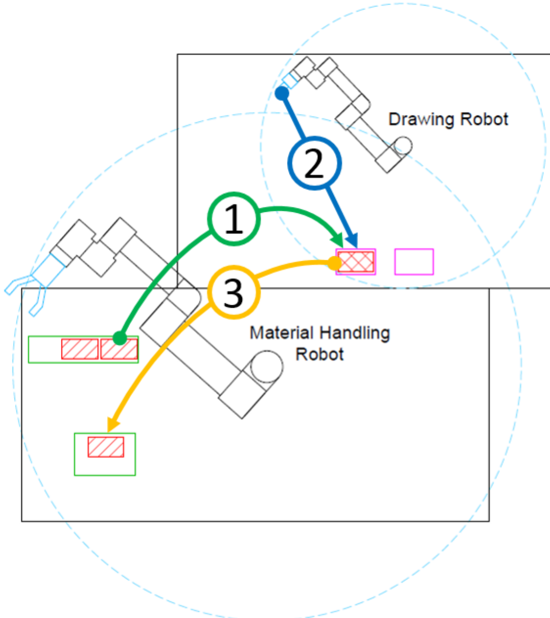

FIGURE 2. THREE TASKS PERFORMED BY ROBOTS IN THE TEST BED: 1) MOVE PART TO THE WORK FIXTURE, 2) DRAW ON THE PART, AND 3) MOVE PART TO OUTPUT.

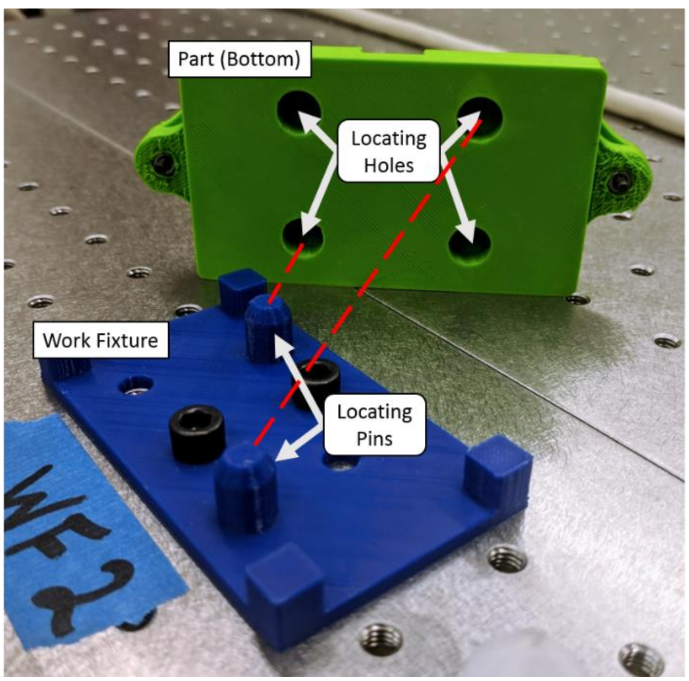

FIGURE 3. WORK FIXTURE WITH LOCATING PINS AND PART (BOTTOM SHOWN) WITH LOCATING HOLES.

The material handling robot is equipped with an electrically-actuated parallel finger gripper-type end effector. Tasks (including waypoints) and task frames (i.e., coordinate systems) are preprogrammed in the robot controller before task execution. The task frames are programmed for each possible pick and place location (i.e., input(s), output(s), and work fixtures). Tasks are assigned to the robot by assigning a pick frame and a place

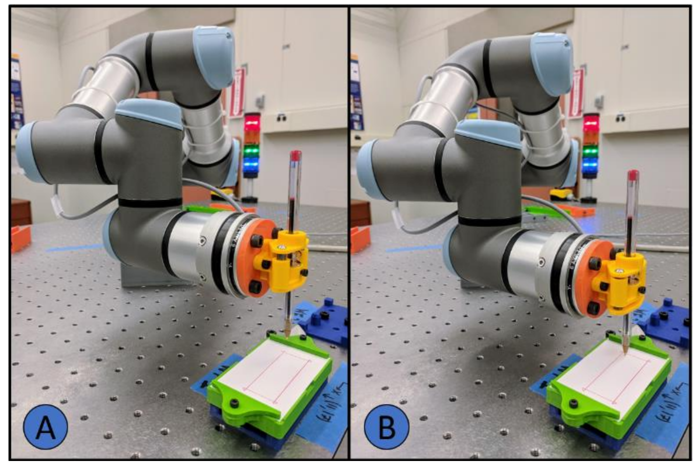

FIGURE 4. COMPLIANT PEN HOLDING END EFFECTOR: A) NOT DRAWING (RESTING POSITION), B) DRAWING (COMPLYING TO PART)

frame. The drawing robot is equipped with a spring-loaded pen holder end effector. The spring-loaded end effector can be seen in the natural resting state (A) and in the drawing state where the spring is compressed (B) in Fig. 4. The drawing robot's task, including all waypoints, are hard-coded relative to a frame dictated by the work fixture (task frame) specified in the task assignment. This results in the same programmed motion profile taking place relative to the work fixture specified by the task assignment. The frame of each work fixture which holds the parts is programmed in the robot controller before task execution. The drawing robot's motion profiles are similar to motion profiles of glue dispensing, deburring, and other processes requiring robot trajectory accuracy.

Coordination, including task assignment, part position monitoring, and process state tracking, is managed by a programmable logic controller (PLC). The PLC tracks the status of each part by monitoring robot task events. Each robot task is composed of three distinct activities: 1) the robot moving into a 'ready' position to perform an action (moving to the start position for drawing or into position to grasp a part); 2) the robot performing the action (drawing, or picking, moving, and releasing a part); 3) the robot moving to a position clear of the part, completing the task, and enabling the robot to be ready to receive a new task. Robot tasks are assigned by transmitting the part number for the task along with pick and place location for the material handling robot or work fixture and task number (i.e., drawing profile, if multiple profiles or part types exist) for the drawing robot. For the current test bed configuration and use case, there is a single part type and single drawing task available for operations (Fig. 5).

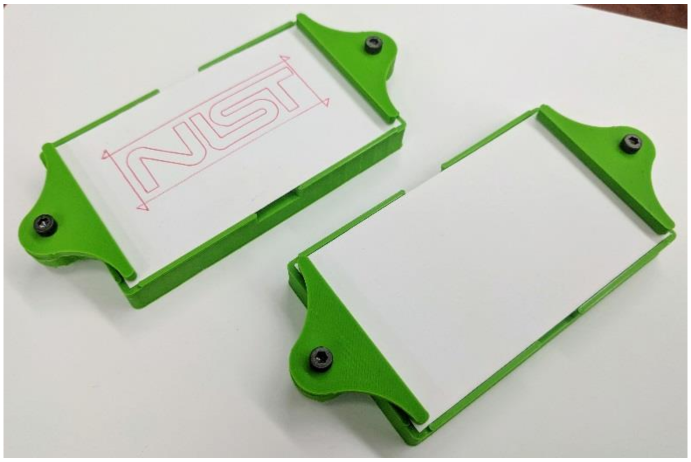

FIGURE 5. COMPLETED PART (LEFT) AND PART AS IT ENTERS THE WORK CELL (RIGHT)

Future configuration plans include the addition of part presence detection at each work fixture, the input, output, and on the material handling robot's end effector to add greater awareness for part tracking and to provide additional data for PHM methods. Though not currently being used, the test bed is designed to accommodate a tray or batch style input and output where a tray with multiple raw parts in multiple locations is fed into the work cell. Additionally, the gravity fed input can be replaced with a motorized conveyor for a more complex input configuration.

HIERARCHICAL DECOMPOSITION

Robot work cells can be complex, posing challenges when designing, deploying, verifying, and validating PHM techniques. Ongoing robot work cell research includes the development of a hierarchical decomposition method to promote advanced monitoring, diagnostic, and prognostics within a robot work cell. The decomposition method is actively being developed and can offer insight where PHM should be implemented within the test bed and use case. The insight gained from the decomposition method will lead to increased equipment and process health awareness which should further inform the PHM evaluation process with the understanding of relationships between elements of the work cell.

The application of this hierarchical decomposition method to the use case is motivated by the desire to bring transparency to how a work cell's physical elements, functional tasks, and corresponding health metrics relate to one another to enhance PHM efficiency [28]. As noted earlier, the initial use case and test bed configuration are purposefully relatively simple as a starting point to prove the overall approach. As this effort continues to make progress, both the complexity of the use case and test bed will expand making it much more difficult to determine the influences and impacts that the health of specific physical elements have on functional tasks along with health metrics.

The overall objective of the hierarchical decomposition method is to develop a cost-effective, methodical approach to guiding the manufacturing community through the PHM design and deployment process when all possible fault and failure modes are not known ahead of time. This method is based upon the Multi-Relationship Evaluation Design framework which generates test-plan blueprints from several categories of input to quantitatively and qualitatively evaluate advanced and emerging technologies at the system, component, and capability levels [29, 30]. The hierarchical decomposition method's foundational elements are helping to manage use case and test bed complexity. At a relatively high level, the steps of the method are:

1. Physical Decomposition – decompose the physical work cell into its constituent components, sub-components, etc. based upon the maintenance-driven boundaries
2. Functional Decomposition – decompose the overall process into its constituent tasks, sub-tasks, etc. based upon control strategy, modularity of the tasks and sub-tasks for reconfiguration or improvement, and what is important to monitor
3. Process and Task Metric Identification – identify all metrics that are captured (or should be captured when a new manufacturing system is being designed) at the overall process level and constituent task and sub-task levels. This task also includes identifying the relationships between these metrics (e.g., which lower level metrics are rolled up into higher level metrics).
4. Risk Identification – identify the sources of risk in the robot work cell in terms of what has been known to go wrong, what could potentially go wrong, the likelihood of something going wrong, and impact of something going wrong.
5. Risk Reduction – explore ways to reduce the risk of work cell faults and failures. Reductions can range from eliminating the potential for the fault or failure altogether (e.g., a robot is known to fail so removing the robot from the design would eliminate this failure) to incorporating preventative (scheduled) maintenance plans and being ready to perform reactive maintenance if something does fail
6. Data to Collect and Collection Approach – identify the necessary data to be collected and the best strategy (e.g., sensor selection, sensor location) in which to do this.
7. Physical Element Metric Identification – identify metrics and measures that can inform on physical system, component, and sub-component health and relate these metrics back to the previously-identified process metrics.
8. Relationship Mapping and Quantification – form the connections up-and-down and across the three (physical, functional, and metric) hierarchical dimensions to document both the influences and the impacts faults and failures can cause throughout the multiple dimensions of a work cell.

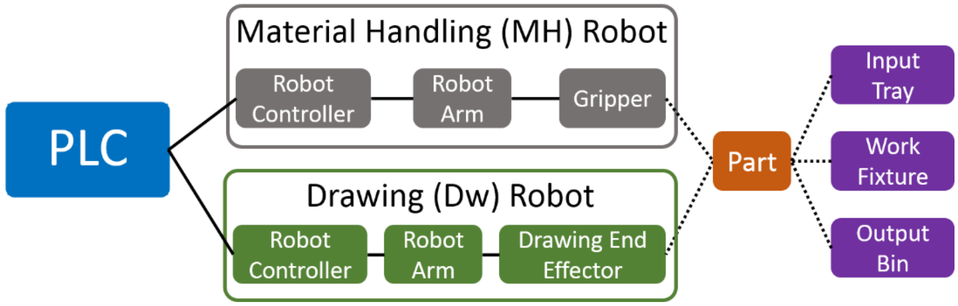

FIGURE 6. PHYSICAL DECOMPOSITION FOR THE USE CASE

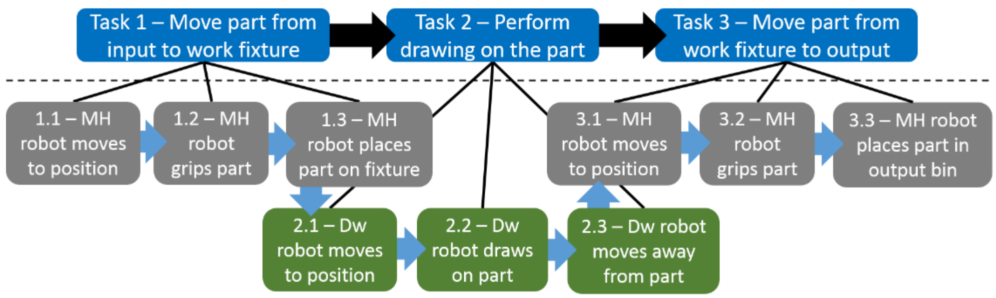

FIGURE 7. FUNCTIONAL DECOMPOSITION FOR THE USE CASE

It should be noted that the first time a user encounters Step 6, they will determine the necessary data to collect based upon the metrics identified in Step 3. Proceeding to Step 7, metrics that are solely focused on physical elements are identified (which may include metrics identified in Step 3). After Step 7, the user returns to Step 5 to determine if risk can be further reduced and Step 6 to identify additional data for collection based upon any metrics identified in Step 5 and the previous iteration of Step 7. The user proceeds to Step 8 after no additional metrics can be identified in Step 7. Step 6 is not the last step because it is possible that the desired data, and corresponding collection strategy, may be unattainable. In that case, the user is going to be limited in the metrics that can be captured and must narrow the focus to specific physical elements.

The first two steps, physical and functional decompositions, are completed for the robot work cell use case and presented at a high-level.

Figure 6 shows the physical element decomposition and begins with the PLC being physically connected to the controllers of both the material handling and drawing robots. The solid lines between the PLC and these two robot controllers indicate that this physical connection is continuous and fixed so long as the work cell is in operation. Both robot controllers are directly connected to their respective robot arms. In turn, both robot arms have a physical connection to their respective end-effectors, the gripper for the material handling robot and the drawing end effector for the drawing robot. Solid lines are used to indicate the fixed connection between these elements. Both the gripper and the drawing end effector directly interact with the parts that enter and exit the work cell. These interactions are dynamic and temporary, based upon the specific task (i.e., material handling, drawing) at hand, so these connections are represented with dashed lines. Several of the physical systems presented in Fig. 6 can be decomposed into constituent components and sub-components based upon their physical construction and what is commonly monitored in a manufacturing environment. For example, both robot arms can be decomposed into each of their six joints, J1 through J6. At minimum, each joint is comprised of numerous sub-components including a motor, a gear reduction, and an encoder. If data is available at a deeper sub-component level, diagnostic and maintenance activities can also be done at this deeper level. Additional details of this physical decomposition will be presented in future efforts.

Figure 7 presents the functional decomposition for the use case at the task and sub-task levels. The overall process is broken down into three specific tasks identical to what was presented in the Test Bed Configuration and Use Case Section of this paper. Each task (1, 2, 3) is then broken down further into three specific sub-tasks (1.1 – 1.3, 2.1 – 2.3, 3.1 – 3.3). Similar to how metrics can be captured to isolate the health of each task level, metrics can also be generated to determine the health of each sub-task. Several fault or failure conditions may warrant sub-task-level inspection to determine where, specifically in the process, errors are occurring. For example, suppose that the cycle time for the overall process is longer than the expected baseline. Upon examination at the task level, a determination could be made as to which specific task(s) are taking longer than expected. Additional examination at the sub-task level can reveal more details of the problem and likely lead to the root cause (e.g., closer inspection of an anomaly in a pick and place operation reveals that sub-task 1.2 – MH robot gripping part is taking longer than expected because the gripper is moving slower than baseline expectations. This could reveal a problem with the gripper and not the positioning of the gripper). Depending upon the information conveyed by the metrics and the inherent complexity of a given process, it is possible that a task, sub-task, and deeper-level investigation may need to occur. Some of the sub-tasks can be broken down further (e.g., 2.2 'Drawing robot draws on part' can be broken down into granular drawing motions). This will be presented in future work.

The remaining steps of the hierarchical decomposition method will be applied to the use case in future efforts. This preliminary application of the method demonstrates some of the expected value of deconstructing the physical features of the work cell and the functional process it enables, providing a foundation on which PHM can be designed and implemented. Applying the next step, 'Process and Task Metric Identification,' requires an understanding of the data that can be captured to inform on the overall process. This leads to the development of a data management and collection approach.

DATA MANAGEMENT AND COLLECTION APPROACH

Devising an appropriate data management and collection strategy is critical to capture PHM data, generate necessary intelligence, and verify its effectiveness. Due to the reconfigurable nature and broad target applications of automation and robotics equipment, there is a large amount of data generated by equipment commonly found in robot work cells for use in PHM methods. The data being generated across automation equipment, and in the test bed, has many data types, units, and sample frequencies. The test bed uses a PLC as both a data aggregator and real-time processor for the data. The PLC is managing two categories of data: 1) external sensor (e.g., discrete presence sensor) and component-generated (e.g., robot) data that is not processed outside the components' internal processing implemented by the original equipment manufacturer. This includes robot-generated data such as joint positions and velocities, temperatures, and controller status; and 2) process-generated data based upon programming on the PLC or other user programmable devices. This data includes part status information, task assignments, and any other calculated values. All PLC data, whether from internal or external sources, is capable of being used in real-time processing within PHM methods being tested and can be recorded for post processing. Though the PLC in the test bed is configured to have access to all data published by the robot controllers in real-time or near-real-time, the controllers do not publish all the data they generate to external devices. Data generated by the robots but unavailable to the PLC is logged (if possible) on the robot controllers and accessible for post processing and analysis.

Specific PLC-generated data that is recorded in the test bed is discussed in the following sub-sections. This internally-generated data includes the building blocks for the OEE metric and can be split into three categories: performance, process, and quality data. Raw data generated by the robots and their controllers will be discussed when the data applications in PHM methods are presented in future work.

Performance Data

Performance measurement can provide data for PHM methods and enable verification of system performance during PHM method testing. Performance is a metric based upon the timing of events in the context of OEE. Performance can be measured at many levels of the system (e.g., the work cell, each robot task, each part). If events, which influence performance of a system, occur on time and/or at a defined rate, the system is performing to specification. The test bed is designed to record timestamps of many state changes and events throughout the execution of the use case.

Timestamps are recorded at predefined state changes and events on the PLC and robot controllers, respectively. Each robot controller and the PLC have their own internal clocks and, due to hardware limitations, the timestamps recorded on each device are relative to their own internal clocks. All timestamp data collected on the PLC is available for real-time calculations and is recorded. The timestamps collected on the robots are only available as recorded data for post-processing and analysis.

The timestamps collected on the PLC correspond to 14 part state changes (to be presented in detail in future work) throughout the processing of a part (see the 'Part State Changes' row in Fig. 8). Timestamps are recorded when PLC-monitored triggers are activated by internal processing (PLC trigger origin) or after the PLC receives an input from a robot controller (robot trigger origin) (see the 'Trigger Origin' row in Fig. 8). Records generated from PLC-originated triggers include parts entering the work cell, assignment of robot tasks, and parts leaving the work cell. PLC-originating triggers are activated by either internal algorithms or sensors which are monitored directly in the PLC Inputs/Outputs (I/O). Records generated from a robot-originated trigger include when a robot begins operating on a part, when the task operation is complete, and when the robot has physically cleared the fixture area and is ready for a new task assignment. Robot-originating triggers are activated by PLC I/O.

In addition to the part state changes that are recorded on the PLC, for each robot task, four events which correspond to unique part state changes are recorded on the robot controllers. The material handling robot records four events for each pick and place operation. There are two pick and place operations for each part, one instance to place the part in the work fixture and another instance to remove the part from the work fixture (see 'Material Handling Robot Events' row in Fig. 8). The drawing robot records four events for the drawing task on each part. The four events correspond to the beginning and end of the three parts of a robot task discussed in the Test Bed Configuration and Use Case section (see the 'Drawing Robot Events' row in Fig. 8).

Each part to be processed is assigned a unique part number as it enters the work cell. The part number is transmitted to the robot controllers when tasks are assigned and each record on the robot includes the part number which is an element in the timestamp records. All timestamp records use the part number as a common index. Records from the individual robot controllers and the PLC can be compiled in post-processing to allow for any individual process segment performance to be calculated.

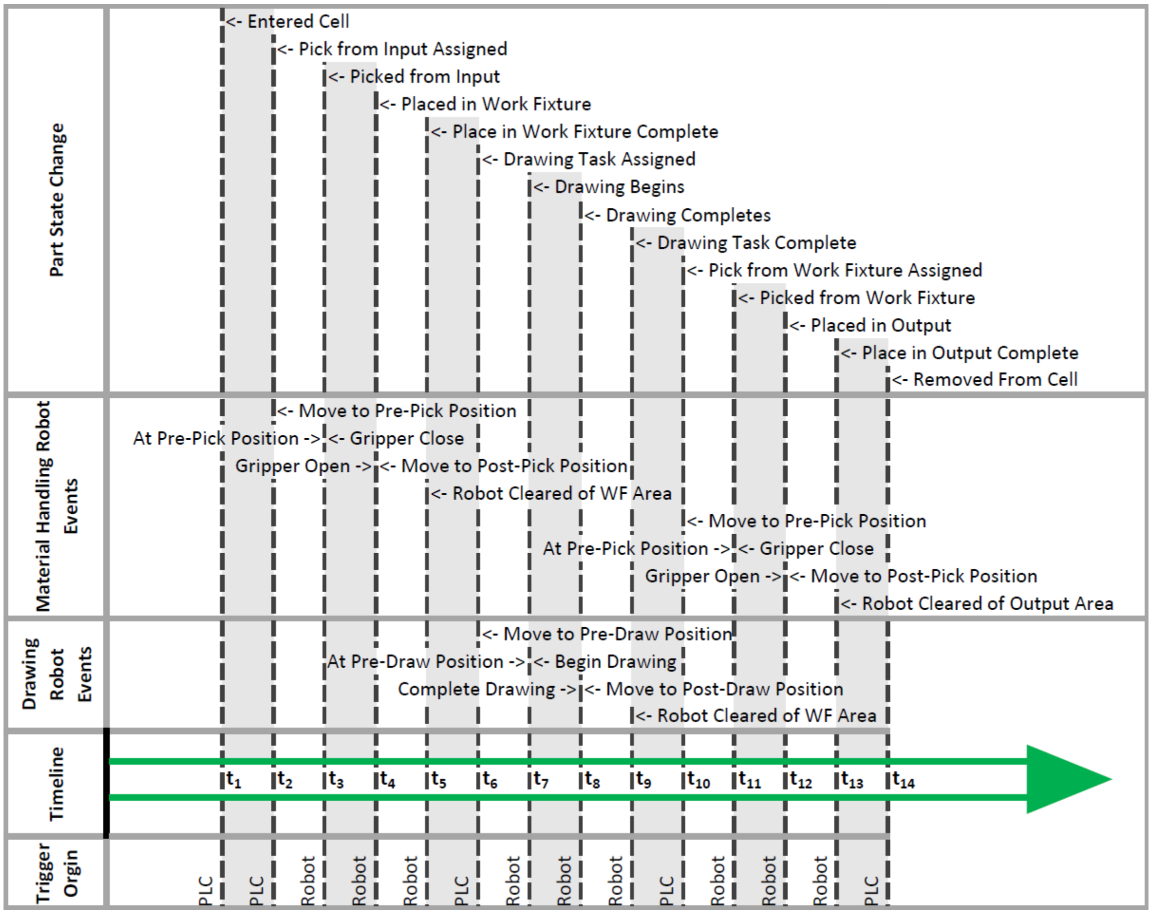

FIGURE 8. TIMELINE OF PART STATE CHANGES AND ROBOT EVENTS.

Process Data

Analysis at the work cell level requires an understanding of the variability of the process taking place to differentiate designed variability vs. degradation variability (caused by process/equipment health changes). In a variable process like the test bed use case, process data is required to provide context to performance data. For example, if a part is being moved by the material handling robot from the input to work fixture 1, it will take a different amount of time as moving a part from the input to work fixture 2 because work fixture 1 and 2 are in different physical locations and the robot moves with constant speed constraints. This timing differential will be seen in timestamps recorded based upon the movement of parts. It may also result in a different total part processing time (from part entering work cell to part leaving work cell) but that is not guaranteed depending on the process, slack time allowance, and existence of bottlenecks.

Process data collected in the test bed are the variable pieces of process information. This includes the input location (single option in the initial configuration presented in this paper), the output location (single option in the initial configuration presented in this paper), the work fixture location, the part number counted from startup, and the part type (task number for drawing robot). A summary of part-related process data being recorded is presented in Table 1. As the test bed is used and more variability is identified and introduced, it is anticipated that more process data will be captured.

TABLE 1. RECORDED PROCESS DATA

Recorded Data	Description
Part Number	Unique identifier for each part processed.
Input Number	Identifies the numbered location where a part entered the work cell. This number is unique to a specific physical location.
Output Number	Identifies the numbered location where a part is placed to be removed from the work cell. This number is unique to a specific physical location.
Work Fixture Number	Identifies the numbered location of the work fixture where the part was placed for the drawing task. This number is unique to a specific physical location.
Part Completed	Boolean identifier if part was completed (PLC interpreted the successful completion of the drawing task)
Part Type	Part-type identifier reserved for the possibility of part type variable processes.

Quality Data

Similar to performance measurement, quality measurement can provide data for PHM methods as well as enable the verification of part quality degradation, or lack thereof, throughout the testing of PHM methods. As work cell components degrade, there may be a direct impact on part quality. This is due to the mechanical allowances built into the system [27]. Quality measures are use case-specific and present differing challenges in their measurement. Many automated processes use some form of automated inspection which generates quality data that is usable in PHM method implementation and assessment.

In this use case, because there is a passive compliance device holding a pen, a degradation of the drawing robot which manifests itself as a positioning error in-line with the compliance will not impact part quality until the deviation from nominal is greater than the allowance provided by the end effector. However, if the robots' degradation manifests itself as a positioning error in the plane parallel with the parts drawing surface, the quality will be directly and immediately impacted.

Two measures of quality have been identified for the current use case:

1. Position of the drawing on the 2D surface
2. Quality of line drawn (e.g., solid continuous, discontinuous)

Two manual measurement methods have been developed. These measurements will provide data that can be used in an offline process to verify the success or failure of PHM methods designed to detect degradations that impact quality. In the test bed, inspections will be done during post processing making the data available for method verification.

To measure the position of the 2D drawing, a transparent template is mated with the completed part, covering the drawing. (see Fig. 9) The transparent template presents a copy of the drawing in the nominal position. The deviation of the completed drawing on the part to the template's nominal position can be measured at any segment of the drawing. For the task currently implemented in the use case, the drawing includes four locations where lines intersect, creating crosshairs for measurement. Alternatively, position can be gauged using a series of transparent templates which have gauging areas on them where if the drawn crosshair is within the gauging lines, the line is at least as accurate as that gauge specification. The quality of the line is manually measured by a person inspecting the completed part.

The quality measures developed will measure the final product and capture both the expected deviations from nominal that are present due to the tolerance stack of physical component position error as well as any additional deviations due to degradations. The nominal variance due to the tolerance stack will be made up of multiple possible component variances including robot repeatability, part-to-fixture mating variation, and the part's quality (is the drawing surface where it should be). For the use case in this test bed, the drawing program is hardcoded with waypoints in a fixed relationship to each other.

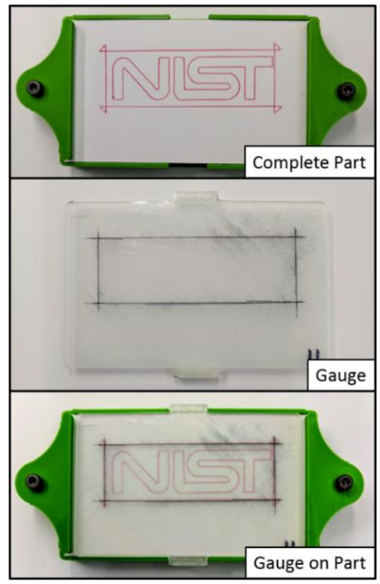

FIGURE 9. QUALITY MEASUREMENT TRANSPARENT GAUGE SHOWN ON AND OFF A COMPLETED PART.

Both fixture and part locations are hardcoded and do not change. Any measure of quality correlates to the repeatability of the robot or the location of the part/drawing surface (this will be further evident upon complete application of the hierarchical decomposition method). This use case was designed to limit the number of potential points of degradation that can impact completed part quality by forcing the robot to perform a repetitive task with hardcoded waypoints.

In a use case where there is dynamic programming, additional sources of error can impact part quality. For example, a vision system could be used to localize a part in a work area. One scenario could dictate the vision system transmit the part's position to the drawing robot which the robot would then use to calculate its kinematics and determine specific waypoints. It would be expected that there would be slight variance in the vision system's interpretation of the part position which would then create greater variation in the completed part. Another example is if the drawing robot did not have a spring-loaded compliance device and instead used force feedback to control pen pressure on the part, any variation in the force feedback could create variation in pen pressure and the final product quality. The domino effect of added variability poses real challenges in monitoring work cell health. It is anticipated that as the research progresses, future test bed configurations and use cases will include vision-based part localization while addressing the challenges of additional variance.

SAMPLE DATA

A sample dataset was collected on the test bed by processing a single part through all 14 state changes presented in the performance data section. Robot and process data were collected as described. In depth analysis of this data and the meaning of it is scheduled for a future publication. Fig. 10 is comprised of

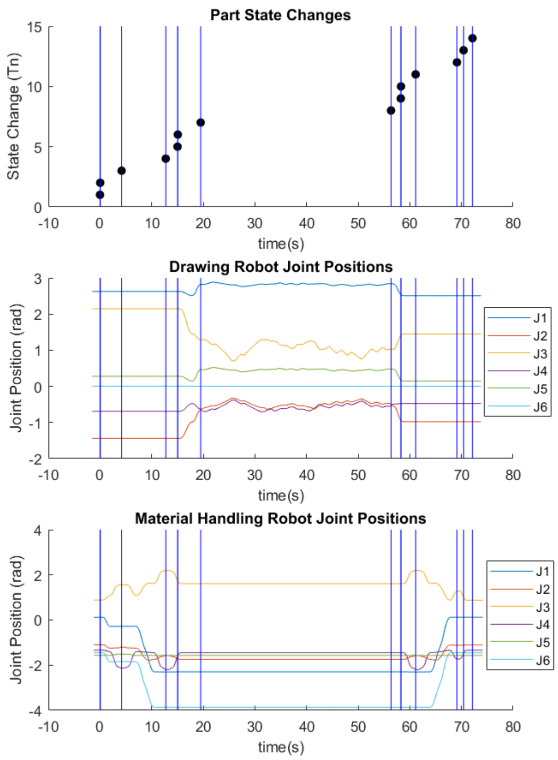

FIGURE 10. TIMESERIES PLOTS OF A SINGLE PART PROCESS SHOWING (TOP TO BOTTOM) PART STATE CHANGES, DRAWING ROBOT JOINT POSITIONS, AND MATERIAL HANDLING ROBOT JOINT POSITIONS.

timeseries plots of a subset of the sample data collected, showing the time of each part state change (vertical lines) along with the positions of each of the six joints on both robots throughout the part process. By capturing part state changes, specific operational regimes can be isolated making it possible to analyze each segment independently and in the context to its operation. In this example each robot is stationary for a position of its time. During these stationary times, any position fluctuations in joint position may be indicative of a degradation of that joint.

This sample was collected without a second part being processed simultaneously to allow a clear view of the expected movements of each robot joint for a single part process. When multiple work fixtures and parts are active within the work cell, timeseries data segments will not be as clear to an observer due to robots performing multiple tasks on multiple parts in a variable order and frequency. The process data collected differentiates the individual segments of robot data and how they correlate to the parts and process. This allows a link to be made between all physical and functional components within the work cell during analysis.

CONCLUSION

A test bed has been built at NIST to collect work cell level data that can be used to verify PHM methods. The use case has been designed as a relatively simple process representative of articulated arm robots performing industrial operations. The data recording structure is such that raw and processed data can be accessed both in real-time and after-the-fact to implement and verify PHM methods. Events throughout the use case process have been defined and allow the recording of timestamps for use in performance measurement. Quality measures have been developed and defined. Process information has been identified and is recorded to contextualize data and the combination of these types of data can be used to inform, monitor, diagnose, and predict failure of elements found in robot work cells. The test bed has been built to serve as a platform to test and evaluate PHM methods developed both at NIST and in industry. This platform has the potential to enable the development of device-agnostic monitoring, diagnostic, and prognostic techniques to enhance manufacturing asset availability. Likewise, the platform promotes unbiased verification and validation of emerging PHM techniques to further inform industry on the capabilities of available technologies. Future work includes characterizing the variability of performance and quality metrics in the base (undegraded) use case, adding capabilities to induce degradation through physical manipulation of components and/or simulation of known degradations, and further applying the hierarchical decomposition method to produce a greater understanding of the physical, functional, and metric relationships within the work cell.

NIST DISCLAIMER

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