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HIERARCHICAL DECOMPOSITION OF A MANUFACTURING WORK CELL TO PROMOTE MONITORING, DIAGNOSTICS, AND PROGNOSTICS

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ABSTRACT

Manufacturing work cell operations are typically complex, especially when considering machine tools or industrial robot systems. The execution of these manufacturing operations requires the integration of layers of hardware and software. The integration of monitoring, diagnostic, and prognostic technologies (collectively known as prognostics and health management (PHM)) can aid manufacturers in maintaining the performance of machine tools and robot systems by providing intelligence to enhance maintenance and control strategies. PHM can improve asset availability, product quality, and overall productivity. It is unlikely that a manufacturer has the capability to implement PHM in every element of their system. This limitation makes it imperative that the manufacturer understand the complexity of their system. For example, a typical robot system includes a robot, end-effector(s), and any equipment, devices, or sensors required for the robot to perform its task. Each of these elements is bound, both physically and functionally, to one another and thereby holds a measure of influence. This paper focuses on research to decompose a work cell into a hierarchical structure to understand the physical and functional relationships among the system's critical elements. These relationships will be leveraged to identify areas of risk, which would drive a manufacturer to implement PHM within specific areas.

INTRODUCTION

Advanced technology continues to emerge at a rapid pace as manufacturers, technology developers, and technology integrators further integrate operations technology with information technology to produce their own iterations of Smart Manufacturing. Smart Manufacturing is focused on bridging and connecting hardware, software, and data to increase operational efficiency, asset availability, and quality while decreasing unscheduled downtime and scrap [1-4]. The successful implementation of these paradigms will lead to greater efficiency within manufacturing operations enabling manufacturers to be more responsive to changing consumer demand and more resilient in the face of increased competition.

Robot systems play a role in many manufacturing environments including automotive [5-7], electronics [8, 9], consumer packaged goods [10], and aerospace [11-13] manufacturing. Smart Manufacturing is having a positive impact on robotic operations occurring on the factory floor. More diverse systems, sub-systems, and components are being connected together which is leading to an increase in robot work cell capabilities. The American National Standards Institute, Inc. (ANSI) defines an industrial robot system to include a robot, end-effector(s), and any equipment, devices, or sensors required for the robot to perform its task [14]. Examples of additional equipment, devices, and sensors include vision and proximity sensors (e.g., camera, laser), safety elements (e.g., light curtain), supervisory controller (e.g., Programmable Logic Controller (PLC)), and other supporting automation (e.g., conveyor belt). Figure 1 presents an example of a robot work cell including some of its key elements.

The integration of these elements and the increase of 'moving parts' generate greater complexity, especially when considering robot-robot and human-robot operations. More complexity leads to more sources of error which can compromise the efficiency and quality of the process. Inclusion of condition monitoring, diagnostics, and/or prognostics (collectively known as prognostics and health management (PHM)) can provide greater intelligence of equipment and process health which can minimize unscheduled downtime, increase efficiency, and improve overall productivity.

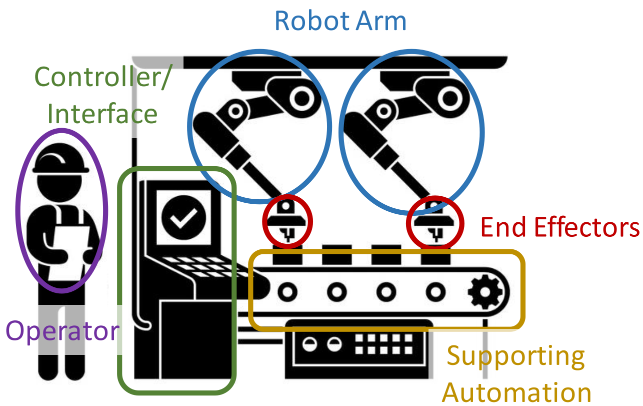

Figure 1. Example Robot Work Cell (MicroOne/Fotolia)

The United States (U.S.) Federal Government has a research focus to advance the means of assessing, verifying, and validating PHM technologies operating within manufacturing environments [15, 16]. This effort is being conducted at the National Institute of Standards and Technology (NIST) and includes a focus on machine tool and robot work cell 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. This paper focuses on decomposing an example robot work cell into an appropriate hierarchical structure through organizing the physical and functional elements such that manufacturers can determine appropriate boundaries with which to overlay condition monitoring, diagnostic, and prognostic technologies. The research is aimed at addressing the question – *How can appropriate physical and functional boundaries be determined within a manufacturing work cell to effectively monitor, maintain, and control the work cell?* To that end, this paper is organized as follows: the Manufacturing Robot Work Cell section discusses typical robot work cells within manufacturing environments and how their complexities, and faults and failures, are evolving with the emergence of new technologies; the PHM section presents background on PHM techniques and technologies that provide monitoring, diagnostic, and prognostic intelligence; the Research Approach section discusses how NIST is organizing its efforts to develop the necessary use cases, test methods, performance metrics, and reference data sets to promote V&V; the Robot Work Cell Hierarchy section presents a proposed method to structure, organize, and delineate physical and functional boundaries to identify areas for PHM inclusion; and the Conclusion section wraps up the paper and presents next steps in the research.

MANUFACTURING ROBOT WORK CELLS

Robot work cells, with industrial robot arms, have operated in manufacturing environments to perform numerous operations including welding, painting, drilling, and material handling [17, 18]. Across the range of robot systems, industrial robotics continues to be a substantial investment by the manufacturing community to improve product quality, increase productivity, and lower costs. The evolution of various technologies, including more intelligent and affordable sensors, displays, end-effector technologies, and control systems has enabled industrial arm-based robot work cells to become more viable options for a larger portion of the manufacturing community [19]. Many of these robot work cells operate for extended periods of time across multiple work shifts. Maintenance strategies for these work cells are either:

- Reactive (fix it when it breaks),
- Preventative (maintenance is performed at specified intervals),
- Predictive (maintenance is performed based upon measured performance and/or health),

…or a combination thereof [20, 21]. Even with regular maintenance, robot system operations will degrade, increasing the potential for faults or failures. Faults and failures can 'naturally' occur through degradation from expected operations, yet the appearance of faults and failures can also be accelerated through a variety of errors. Faults and failures can be related to hazards; faults and failures can produce hazards and the presence of hazards can lead to faults and failures. The Occupational Safety and Health Administration (OSHA) has identified seven potential robotic work cell hazards [22]. A subset of these hazards are due to faults or failures:

- Human Errors – Includes erroneous commands entered into the teach pendant by the operator, ignoring/misinterpreting data presented by the system, and failure to follow all safety protocols
- Control Errors – Includes errant controller code and degradation of controller hardware
- Mechanical Failures – Includes degradation of motors and gears of the robot arm and actuators, motors of the end-effector, and faulty sensors providing inaccurate data to the controller
- Environmental Sources – Includes pronounced changes in temperature, humidity, and sunlight (which can impact certain sensor readings)
- Power Systems – Includes power surges and power loss

There is no single way that these faults and failures can be classified. Some faults and failures are the root causes (a sensor has a loose wire and is therefore reporting erroneous data to the controller) while other faults and failures emerge once the root cause has occurred (a robot arm is hitting a box because the controller is telling the arm that nothing is in front of it because the proximity sensor has a loose wire and is reporting that the area is clear of obstacles). Three principle categories have been developed to classify faults and failures [19] [23-25]. These categories are designated:

- Faults – Typically design defects, inaccurate signals, or incorrect decisions that impact the system's ability to function properly. Some faults may accelerate the degradation of a component or sub-system (e.g., a robot arm returns a fault when it is over-loaded. Excessive over-loading of the robot arm can result in increased wear and tear on gears and motors).

- Soft Failures – Degradation or wear and tear that has resulted in decreased process efficiency, productivity, and/or product quality. Soft failures, if left unaddressed, can lead to hard failures. An example of a soft failure would be a degraded motor in a robot arm that is now limited in the speed at which it can move. The robot may still be capable of completing its required task, yet it may take more time than specified.
- Hard Failures – Degradation or wear and tear that has resulted in breakage that has compromised the productivity and/or quality of the process. Hard failures are typically indicated with the system being in a frozen/shutdown state or in a state of performing egregious behaviors. Examples of hard failures include a complete motor failure where a joint has gone limp or a controller error where the robot no longer moves.

The different types of faults and failures presented above highlight the complexity of robot work cells operating within manufacturing environments. Additional complexity is continually being added to work cells with the inclusion of more collaborative robotic systems – robots working with other robots and robots working in closer proximity to humans [26]. It becomes much more important to accurately monitor, diagnose, and predict faults and failures in work cells when humans are operating in relatively close proximities.

Further complexity in a robot work cell stems from any reconfiguration(s) that occur throughout the life of the work cell and its key components. Different types of faults presented above highlight the complexity of robot work cells operating within manufacturing environments. Consider a robot work cell that is tasked with material handling operations (e.g., a robot that manipulates boxes off of a conveyor belt). Over time, components and sub-components will have to undergo a range of maintenance activities to maintain productivity and quality targets. At some point, it's likely that it will be more cost effective to replace one of the key components or sub-components with a new one as compared to repairing this component. Suppose that the 20-year-old robot is now replaced with a new robot. It's likely that the new robot will have greater capabilities than the old robot (unless you find a new iteration of the same robot). After integrating the new robot into the work cell, it's discovered that the work cell is operating at its expected performance as compared to when the old robot was in place and operating to specification. However, it is possible that the new robot is faster, more accurate, capable of lifting heavier loads, etc. With that being the case, the operator has the potential to increase the productivity of the work cell and/or quality of the work cell's output. If/when the operator takes advantage of the new robot's capabilities, the robot, which may have been the 'weak-link' in the prior iteration of the work cell, may now be the strongest link in the work cell. In this situation where the robot work cell was reconfigured to accommodate a new robot arm, all of the relationships between the robot arm and other key components (e.g., end-effector, controller, sensors, safety systems) have changed [since the old arm was replaced with a new arm]. Not only does baseline performance of the robot work cell need to be reestablished with the new arm, the relationships between any component interfacing with the robot need to be understood so the degradation and wear and tear on these elements can be similarly understood. An analogous situation occurs when the work cell must be reconfigured to produce a different part. The work cell is likely to undergo some type of hardware and/or software reconfiguration which thereby alters the relationships among key physical and functional elements. Changing relationships will change how the various elements degrade over time.

Given the robot work cell's complexity, PHM can offer monitoring, diagnostic, and prognostic capabilities to track key performance metrics to examine the impact of the many relationships present in the work cell with respect to the relationship influence on overall system, process, and equipment health.

PROGNOSTICS AND HEALTH MANAGEMENT

Advancing PHM in the manufacturing environment can lead to substantial savings for an organization. PHM may ultimately enable a machine or system to self-diagnose and self-heal with enough intelligence to be both aware of its current health and make an appropriate decision given both its state and goals. This is known as the proactive/intelligent maintenance strategy and is the topic of substantial research [27-29]. Current PHM technologies are enabling the three afore-mentioned maintenance strategies (reactive, preventative, and predictive) within a range of manufacturing environments [30-34] .

PHM research has led to studies and reviews that compare existing PHM methods along with highlighting their strengths and limitations [35-38]. More specifically, reviews of PHM-based standards have also been conducted [39-41].

Collectively, PHM methods can be summarized below in Fig. 2. Each of these methods can be applied in vastly unique ways given the uniqueness of each manufacturing facility, subsequent work cells, etc.

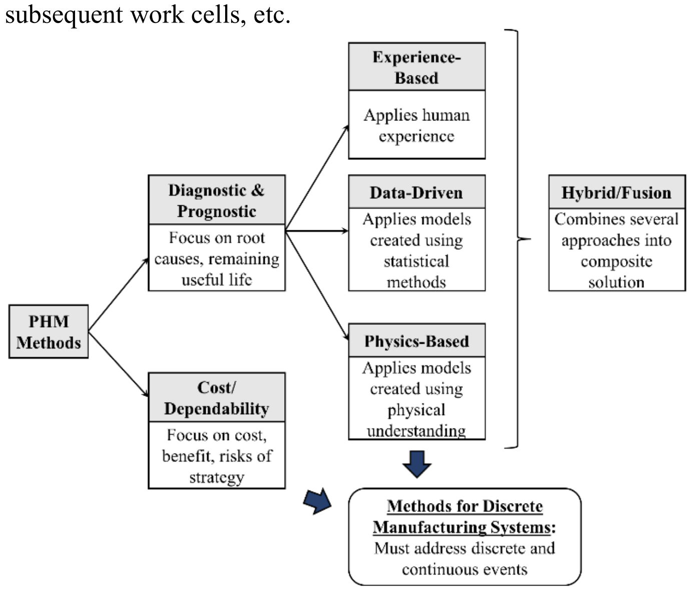

Figure 2. Description of general PHM methods [38]

Literature reviews and direct discussions with the PHM community (e.g., PHM technology developers, PHM technology integrators, and manufacturers as the end-users of PHM) have highlighted a need to improve the existing maintenance strategies that are currently used within a factory. Most manufacturers employ a mix of reactive and preventative maintenance strategies to ensure sufficient operations. Relatively few manufacturers have implemented predictive maintenance strategies to enhance their monitoring, diagnostic, and prognostic capabilities. Minimizing reactive maintenance while enhancing (ideally, optimizing) preventative and predictive maintenance requires a greater understanding of where and how PHM can be implemented in the manufacturing environment. As PHM becomes more important to the manufacturing community, more people have recognized the importance of developing and improving various PHM implementations. One challenge is that the PHM community is largely void of methods to verify and validate the capabilities of these emerging PHM techniques.

RESEARCH APPROACH

The NIST research team is taking a methodical approach to develop the necessary use cases, performance metrics, test methods, reference datasets, and software tools to provide a means of verifying and validating PHM within manufacturing robot work cells [16, 39]. Given the complexity of a typical robot work cell, it is important to initiate the research in a basic manner where variables, especially those that influence system, process, and equipment health, are minimized. This breeds the development of a basic robot work cell. For NIST's research efforts, this takes the form of a robot arm and its controller where the robot is hard-coded in its operations as opposed to being influenced by external sensing, safety, or human inputs. This basic work cell is being used by NIST as the foundation for the development of a quick health assessment methodology that will allow manufacturers to verify the health of their robot in terms of its positional accuracy [19]. Besides simplifying the robot work cell, it's also important to limit the research focus to a specific area(s) of PHM to avoid too much complexity too soon. While the complexity of the work cell can be considered the first axis of influence, the second axis that influences complexity and difficulty of the problem is that of the specific PHM and decision-making focus (see Fig. 3). NIST's research efforts will increase in complexity by adding additional, manufacturing-relevant components to the work cell and employing diagnostic and prognostic techniques at different levels of the work cell. Further using the NIST research example, the quick health assessment methodology is aimed at monitoring the health of the robot arm (in terms of its positional accuracy), offering some diagnostic information (with respect to the health of specific joints), and providing intelligence to update the robot's control strategy accordingly (i.e., compensating for performance errors due to health degradation).

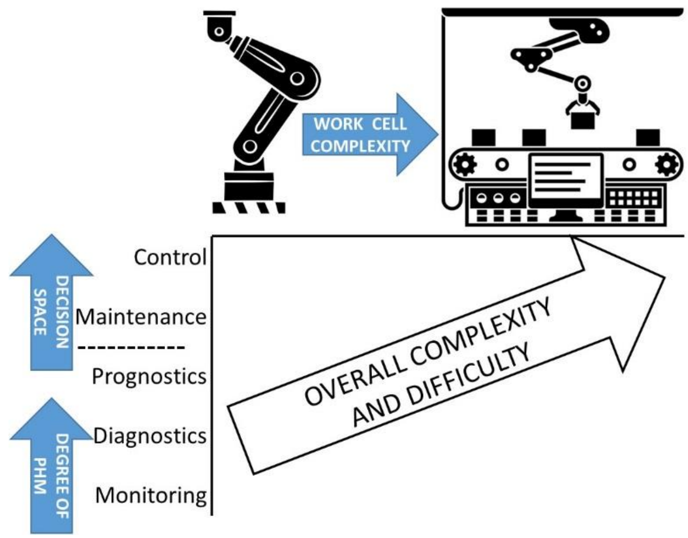

Figure 3. NIST Research Approach (Funway5400, MicroOne/Fotolia)

As NIST's research efforts expand, so too will the complexity of the robot work cell and the degree to which PHM and the decision space are included. This will lead to greater complexity and more challenging research. Embracing greater complexity and difficulty requires a thoughtful way of organizing and structuring the complexity of the robot work cell. A single robot arm and its controller, without any other elements, are still somewhat complex. Adding external sensors, end-effectors, safety systems, supporting automation, etc. makes it more complex. A hierarchical model is proposed to promote the structuring and organization of the overall work cell, its constituent physical components, and sub-components. Likewise, this physical hierarchy has a mirror that maps the system's overall capabilities and building-block functions. The development of this hierarchy will make it easier to identify boundaries within the work cell for the inclusion and advancement of PHM.

ROBOT WORK CELL PHM ANALYSIS HIERARCHY

A robot work cell can be viewed as a hierarchy of systems and components. This type of physical decomposition is both critical in the design of a new system and also understanding the relationships and interactions of an existing system as defined in the National Aeronautics and Space Administration's (NASA's) Systems Engineering Handbook [42]. Building upon this systems engineering approach, Multi-Relationship Evaluation Design (MRED) was developed as a means of decomposing a complex system into its key physical components and functional capabilities for the purpose of strategically evaluating the performance of specific sub-systems, components, and capabilities at differing levels of the system [43-47]. Although MRED is focused on performance evaluation, it can be leveraged to hierarchically decompose the physical components and sub-components, in concert with the system's capabilities to delineate boundaries for PHM. Figure 4 presents an abstract hierarchical decomposition of a physical system based upon the MRED effort. Note that the physical makeup of the system is typically more complex than the three levels (*System*, *Component,* and *Sub-Component*) where there could be sub-system levels before reaching the component level. Adapting the MRED definitions of the below key terms for this effort becomes:

- *Component* – An essential part or feature of a *System* that contributes to the *System's* ability to accomplish a goal(s).
- *Sub-Component* – An element, part, or feature of a *Component* that can be isolated for the purpose of maintenance or replacement.
- *System* – A group of cooperative or interdependent *Components* forming an integrated whole to accomplish a specific goal(s).

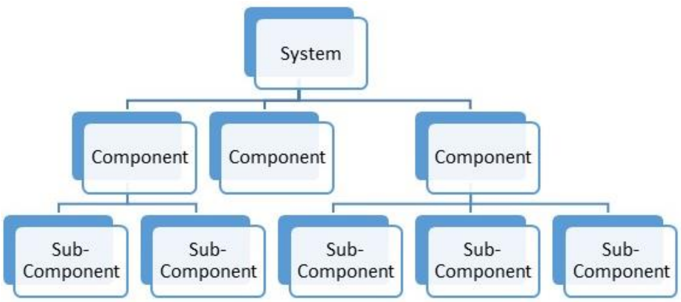

Figure 4. Hierarchical Physical Decomposition

Distinctions between what is a *System, Component,* and *Sub-Component* are based upon several key factors including: 1) what elements are physically separate allowing them to be independently maintainable or replaceable and 2) the logical/functional connections between multiple elements. The process of distinguishing elements from one another will be clarified later in this section through the discussion of the two-arm robot work cell example.

From the MRED effort, each of these physical levels are defined as *Technology Test Levels*. Considering the focus of this NIST-led effort, it would be more appropriate to define these levels as *Monitoring, Maintenance, and Control Levels* (*MMCLs*).

Figure 5 leverages additional terms from MRED that are applied to this research effort and would be *MMCLs*.

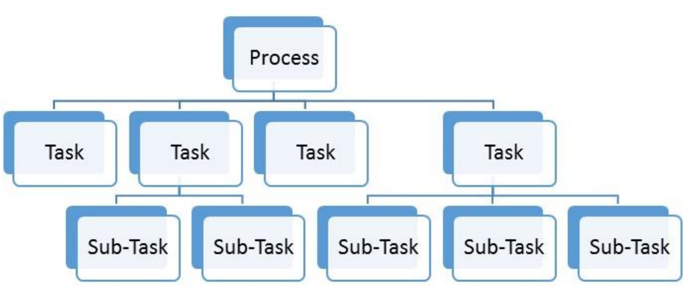

Figure 5. Hierarchical Functional Decomposition

- *Process* – The overall activity that the *System* is configured to perform.
- *Task* – A specific activity within the overall *Process*. A *System* performs a single *Process* that is made up of one or more *Tasks.* A *Task* is enabled by either a single *Component* or multiple *Components* working together.
- *Sub-Task* – A building block function of a *Task*.

Coupling in the functional concept of a *Task*, the relationship between physical and functional elements is presented in Figure 6. Considering that *Sub-Components* and *Sub-Tasks* are building block elements of *Components* and *Tasks*, respectively, Fig. 6 could be substantially expanded to include these *Sub-* level elements.

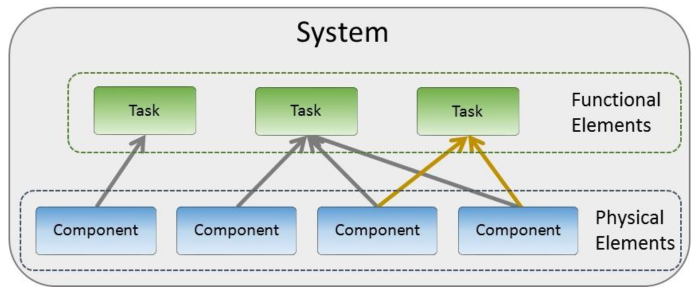

Figure 6. Component and Capability Mapping Diagram

MMCLs highlight user-defined areas that 1) designate specific physical elements (i.e., *System, Component, Sub-Component*) and/or functions (i.e., *Task, Sub-Task*) that should be monitored to track current and predict future health states; 2) identify physical elements for maintenance to be performed pending the results of monitoring efforts; and functions whose control strategies need to be updated given current and predicted health. Each *MMCL* has one or more metrics that are monitored and reviewed for maintenance and control decisions. Likewise, metrics monitored at one level may be leveraged for maintenance or control decisions at another level. Given the uniqueness of every system, metrics are also user-defined.

The hierarchical decomposition is applied to a two-arm robot work cell. Figure 7 identifies the key *Components* within the *System.* This figure will also be referenced to highlight the key *Tasks* that produce the overall *Process*. The following steps are prescribed to decompose an existing *System* to determine the *MMCLs*.

1. Identify the objective/goal of the *System*.
2. Identify the *Process* that the *System* is to perform.
3. Identify the physical boundaries of the *System* necessary for decomposition. The boundaries are based upon what is necessary to physically accomplish the objective/goal. This step may be performed simultaneously with Step 2.
4. Break-down the *System* into *Components*. Physical boundaries of *Components* can be discretionary based upon what can reasonably be physically separated for the purposes of repair and replacement.
5. Breakdown the *Components* into *Sub-Components*.
6. Break-down the *Process* into constituent *Tasks*.

7. Break-down the constituent *Tasks* into *Sub-Tasks*. *Process* and *Task* decomposition is influenced by what can be functionally separated from a control perspective.
8. Determine the performance metrics that are necessary to determine if the objective/goal is accomplished. These metrics would be similar to NASA's *Measures of Effectiveness* [42]. *"Measures of Effectiveness* are the operational measures of success that are closely related to the achievement of mission or operational objectives in the intended operational environment" [42].
9. Determine any performance metrics that are necessary to assess whether the *Process* is successfully completed as specified. It's possible that some of the metrics identified in Step 4 also assess the overall *Process* which would present metrics that can assess both the objective and the *Process*. These metrics would be similar to NASA's *Measures of Performance* which "characterize physical or functional attributes relating to the *System"* [42].
10. Determine the metrics that are necessary to assess the success of *Tasks* and *Sub-Tasks*. Likewise, determine any additional metrics necessary to assess the health of *Components* and *Sub-Components* that make-up the overall *System* and influence the *Process.* These metrics would be most comparable to NASA's *Technical Performance Measures* which are considered critical and measurable performance attributes that can be monitored [42].

Figure 7. Two-arm Robot Work Cell – Key *Components* (MicroOne, Motorama/Fotolia)

Steps 1 through 9 present the hierarchical decomposition of a pre-existing *System* and *Process.* It is important to note that some of the steps may be done simultaneously given that the *System* is already known. Likewise, some of these steps are presented in brief due to space limitations. The importance of going through these steps is to capture and organize the structure of the *System* and the *Process* to identify the most ideal areas, within the structure, to incorporate PHM. The remainder of this section decomposes the example two-arm robot work cell according to these steps. The following section begins the discussion of how PHM can be integrated into a decomposed *System*.

Step 1: The objective of the *System* presented in Fig. 7 is for parts to be marked in a specific location and sent to the next station in a specified amount of time. Since the example work cell is designed as an industrially-relevant use case, the marking of a part is representative of a robot moving to a precise location with respect to the part and altering the part to support the finished product. Specifically, having a robot perform this type of activity is similar to having a robot drill a hole or perform a spot weld.

Step 2: The *Process* that the *System* performs is for two robots to work together to manipulate parts off of an incoming conveyor system, apply a mark to a precise location on the incoming parts, and return the parts to an outgoing conveyor system.

Step 3: The physical boundaries of the *System* begin with the part entering the work cell and end with the part leaving the work cell. The physical boundaries do not include the room/building that the work cell resides. Specifically, the boundaries of the *System* are defined by its key *Components*.

Step 4: The key *Components* of the work cell, presented in Fig. 7, are the two robot arms (A and B), their respective controllers (C_A and C_B), their respective end-effectors (E_A and E_B), the inbound conveyor (D), the outbound conveyor (F), and the supervisory PLC (G). Other key *Components* not shown in Fig. 7 include a vision sensor that detects the position and orientation of parts on the inbound conveyor, D, any safety elements as deemed necessary based upon the expected proximity of human operators/supervisors, and the fixtures that hold parts while they are being marked.

Step 5: Each of the two robots can be broken down into their six constituent joints – the base, shoulder, elbow, wrist 1, wrist 2, and wrist 3, and the robot controller. Each of the six joints could be further broken down into their constituent motors and encoders. The conveyor is decomposed into its physical structure, motor, and encoder. Depending upon the safety system configuration (e.g., safety mat(s), light curtain(s)), these can be decomposed further.

Step 6: The key *Tasks*, shown in Fig. 9, underscore the *Process* flow of the *System*. The *Process* begins with *Task 1* – parts move on the inbound conveyor, D, until they arrive at a pre-determined location within the reach of robot arm A. *Task 2* involves robot arm A grasping the nearest part with its gripper, E_A, and placing it on the fixture next to robot arm B. *Task 3* calls for robot arm B to 'mark' the fixture part with its tool tip, E_B. After the fixture part is marked, *Task 4* calls for robot arm A to remove the part from the fixture and place it on the outbound conveyor, F. *Task 5* calls for Conveyor F to move the 'marked' part to its next destination. It is important to note that this robot work cell (i.e., the *System*) is being designed to be inclusive of numerous *Components* and *Tasks* commonly found in manufacturing environments according to case studies and site visits [20, 21, 48].

Step 7: Each of the afore-mentioned *Tasks* presented in Step 6 can be broken down into *Sub-Tasks*. For brevity, only *Task 1* will be broken down into *Sub-Tasks*. These *Sub-Tasks* are:

- *Task 1, Sub-Task 1* – A part on the incoming conveyor moves until it comes into the field of view of an overhead vision sensor (which is above the end of the conveyor closest to Robot A)

- *Task 1, Sub-Task 2* – When a part is detected in the field of view of the overhead vision sensor, the sensor indicates to the Programmable Logic Controller (PLC) that a part is present [in the vision sensor's field of view].
- *Task 1, Sub-Task 3* – The PLC sends a signal to the conveyor telling it to stop.
- *Task 1, Sub-Task 4* – The PLC sends the vision sensor data to Robot A's controller that includes the position and orientation of the part in view.

Step 8: The performance metrics that are defined to indicate whether the overall objective has been accomplished include:

- *Takt Time* – This metric is measured in seconds and represents the frequency a completed part exits the work cell.
- *Mark Accuracy* – This metric is measured in millimeters and represents how far from the part's center the mark is made

Step 9: The performance metrics that are defined to indicate the successful completion of the *Process* include:

- *Cycle Time* – This metric is measured in seconds and represents the total amount of time a part spends in the work cell (i.e., the total time it takes a part to complete *Tasks 1* through 5).
- *Quality Degradation* – This metric represents the change in quality that a part experiences as it runs through the work cell. For example, parts could be accurately marked and run through the work cell rather quickly, yet Robot A could be damaging parts while it is manipulating them or Robot B is making erroneous marks in addition to accurately marking the top of parts.

It is reasonable that *Takt Time* and *Mark Accuracy* could also be considered *Process*-level performance metrics. Overall Equipment Effectiveness (OEE) could also be another metric used at the objective level and/or the *Process* level [49]. However, the effectiveness and value of this metric has been a recent topic of debate [50]. The value of OEE for this specific work cell is being discussed in comparison to simply using its aggregate metrics: asset availability, productivity, and quality.

Step 10: The performance metrics that are defined to assess the *Tasks* and *Sub-Tasks* are too numerous to be presented. They include a range of time measurements with respect to robot, part, and conveyor movements. Additional metrics include accuracy of the vision system and the robot movement.

The robot work cell presented in Fig. 7 can be characterized in the hierarchical physical decomposition presented in Fig. 8. This decomposition presents key physical *MMCLs* that seem reasonable to monitor during the afore-mentioned manufacturing process based upon the critical contributions of each *Component* to the *System*. The organization of this figure could be challenged. For example, it would be plausible for the Supervisory PLC, G, to be placed at the top of the hierarchy (situated where 'Robot Work Cell' appears) given that the PLC will be the 'brains' of the manufacturing process and coordinate all activities. From a control perspective, this would be a reasonable structure. Given that this decomposition is purely physical, the PLC is placed on the same level as other key *Components* since, physically, none of the other *Components* is located inside of the boundaries of the PLC. To further extend the physical decomposition, it was noted earlier that each robot could be broken down further into individual joints. Each of these joints could be broken down further into their respective gears, motors, and wiring, and then down further into shafts, nuts, bolts, etc. Physically decomposing this robot work cell down to the nuts and bolts level is not practical from the perspective of monitoring, maintenance, and control. It may be useful to stop the physical decomposition at the level of the robot arm or it may be useful to go down to the next level that identifies specific joints; this decision is directly influenced by historical knowledge of what can practically be monitored, where problems occur, and how maintenance is performed. In this specific work cell, it is beneficial to decompose the work cell down to specific joints. Further, each joint would be further decomposed into its constituent motor, encoder, current sensor and gearing. Again, the full decomposition is not visualized in this paper.

Performing a *Component* and *Task* mapping adds clarity with respect to the relationships of the *MMCLs*. Figure 9 presents this initial mapping. Only *Task 1* and *Task 4* are mapped out between the *Component* and *Task* levels. *Tasks 2, 3,* and *5* are not shown due to space limitations. Several key *Sub-Components* are added for each robot, yet a majority of *Sub-Components* and all of the *Sub-Tasks* are not shown for brevity. It is evident that there are many relationships between the physical and functional levels. Likewise, some physical elements contribute to multiple *Tasks*. Now that Steps 1 through 10 are complete for the robot work cell, *System* and *Process* have been sufficiently decomposed to more easily identify the *MMCLs* based upon fault and failure knowledge of the individual elements and historical data of the work cell, if the work cell has been in service and data has been captured prior to this decomposition.

INFLUENCE OF RISK ON THE HIERARCHY

As discussed in the earlier section, the hierarchies can be challenged. It is possible that the hierarchies will evolve as the risk of potential faults and failures is understood. These hierarchies could also impact the *MMCLs.* If a *System, Component, Sub-Component, Task,* or *Sub-Task* is considered low risk (i.e., very unlikely to fail, and if it does fail, the failure will have negligible impact and/or be very easy to remedy) in the overall manufacturing process, then it is unlikely that this *MMCL* will be independently bounded. Conversely, if a *MMCL* is considered high risk (i.e., very likely to fail or if it does fail, the failure would have a severe impact on the manufacturing process), then it is very likely that the *MMCL* will be clearly specified so it can be monitored, maintained, and/or controlled.

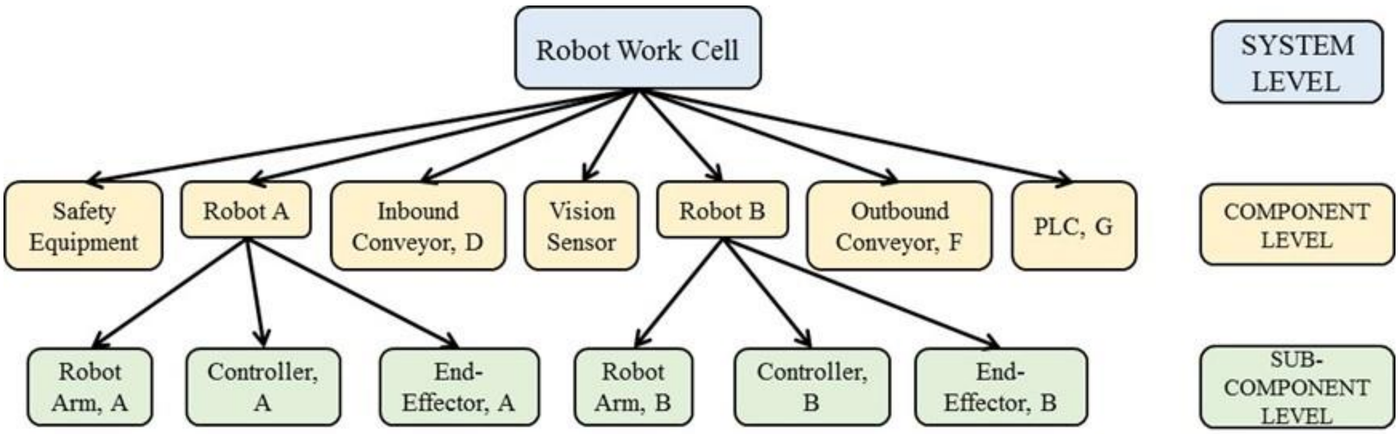

Figure 8. Physical Hierarchical Decomposition of Robot Work Cell

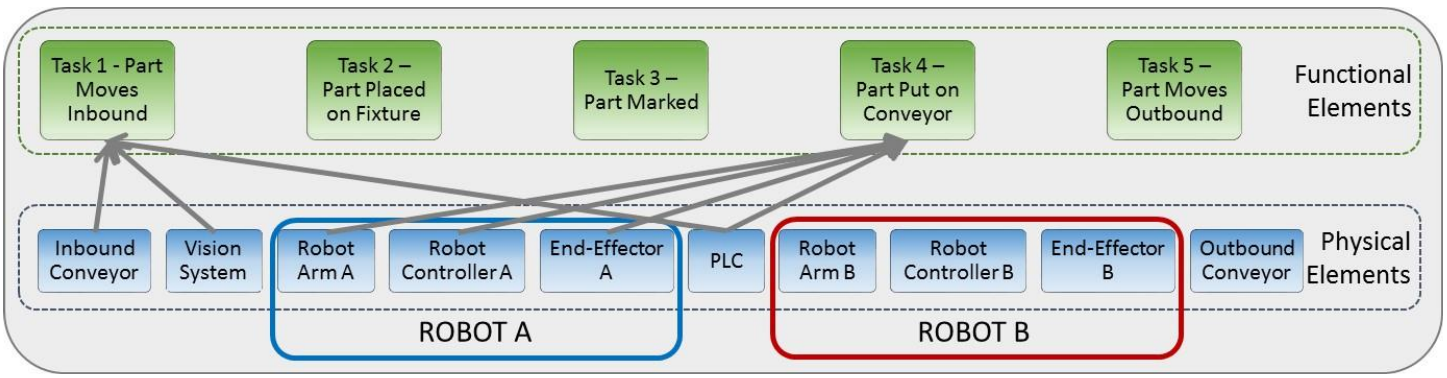

Figure 9. Component and Task Mapping

Figure 10 presents an example risk matrix. This matrix presents risk (low, low medium, medium, medium-high, and high) in

LIKELIHOOD \ IMPACT	Negligible	Minor	Moderate	Significant	Severe
Very Likely	Low Med	Medium	Med Hi	High	High
Likely	Low	Low Med	Medium	Med Hi	High
Possible	Low	Low Med	Medium	Med Hi	Med Hi
Unlikely	Low	Low Med	Low Med	Medium	Med Hi
Very Unlikely	Low	Low	Low Med	Medium	Medium

Figure 10. Risk Matrix [51]

terms of likelihood (very unlikely, unlikely, possible, likely, very likely) and impact (negligible, minor, moderate, significant, severe). Organizations use this matrix to evaluate levels of risk so they can clearly differentiate the various types of risk present. This type of risk matrix can be paired with the *System* and *Process* decompositions to indicate the varying levels of risk that a *Component, Sub-Component, Task,* and *Sub-Task* will fail during its designated manufacturing process. In practice, it would be expected that an organization would not tolerate any high risk, or even medium high risk, where the potential, for such faults and failures would be designed out of the system and therefore eliminated. Different organizations apply the risk matrix in terms of quantifying likelihood and impact values. The following guidelines are presented:

- Likelihood – corresponds to a percentage or frequency that the *MMCL* will experience a fault or failure. Values can be quantified as percentages (e.g., Very Likely – greater than 50 % chance of fault/failure occurrence, Likely – between 25 % to 50 % chance of fault/failure, Possible – between 10 % to 25 % chance of fault/failure, Unlikely – between 1 % to 10 % chance of fault/failure, Very Unlikely – less than 1 % chance of failure) or as frequencies (e.g., Very Likely – fault/failure may occur once/day of operations, Likely – fault/failure may occur once/week, Possible – fault/failure may occur once/month, Unlikely – fault/failure may occur once/year, Very Unlikely – fault/failure may occur once/lifetime)
- Impact – corresponds to the significance that a fault/failure of an *MMCL* will have on the operations. Impacts can be quantified in terms of loss of quality or

productivity, which can both be turned into loss of dollars. Example quantifications of impact could be Severe – *Process* is offline for greater than a week, Significant – *Process* is offline between one day to a week, Moderate – *Process* is offline between an hour to a day, Minor – *Process* is offline between 10 minutes to an hour, and Negligible – *Process* is offline for less than 10 minutes. Some risk matrices that are actively used quantify impact in terms of personnel injury. This effort is focused on fault/failure impact to the manufacturing process and not impact on personnel.

The hierarchical *System* and *Process* decompositions provide a technology developer, technology integrator, or manufacturer the means of delineating the boundaries of *MMCLs* of importance. Establishing these boundaries must be coupled with an understanding of how much risk each *MMCL* carries with them so that the appropriate PHM technique(s) can be applied. This paper lays the foundation for this research effort where future work has begun to add greater clarity to this process.

FUTURE WORK

Building upon this effort, the next step in this research is to further link *MMCLs* across the physical and functional hierarchies. Further understanding these linkages will enable technology developers, technology integrators, and manufacturers to identify key relationships between *MMCLs*. This will enable additional guidelines to be provided to support strategic inclusion of PHM through the *System* and *Process*.

Next, common robot work cell faults and failures will be mapped back to the physical and functional hierarchies. This will include highlighting which faults and failures are the root cause vs. the faults and failures that result from a connected *MMCL* failing. In parallel with linking common faults and failures, metrics will also be identified and integrated that enable monitoring, diagnostics, and prognostics to occur.

CONCLUSION

Technology developers, technology integrators, and manufacturers must be strategic in their implementation of monitoring, diagnostic, and prognostic techniques within their manufacturing processes. Insufficient PHM can lead to costly faults and failures that compromise the manufacturing process, and, ultimately, the organization's health. Too much PHM can be expensive in terms of the materials (e.g., sensors, computers) and labor (e.g., personnel to design the PHM system, develop new algorithms, monitor the PHM system). This builds the foundation for a process that will aid in the strategic placement of PHM throughout a manufacturing process by promoting the delineation of clear boundaries across *MMCLs* and defining PHM priorities through risk assessment. PHM techniques are implemented largely because there is a risk of a fault or a failure. If the risk cannot be eliminated, then the organization must weigh the value of PHM vs. the value of realizing the fault or failure. No PHM technique is 100 % accurate or perfect, yet PHM's implementation within a range of manufacturing environments has been documented in terms of having positive impacts. The process presented in this paper would add greater rigor to the integration, and extent of, PHM across a manufacturing process.

NIST DISCLAIMER

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