Published in final edited form as:

J Manuf Syst. 2018 ; 48(Pt C): . doi:10.1016/j.jmsy.2018.03.002.

Developing a hierarchical decomposition methodology to increase manufacturing process and equipment health awareness

Brian A. Weiss^{a,*}, Michael Sharp^b, and Alexander Klinger^a

^aNational Institute of Standards and Technology, 100 Bureau Drive, MS 8230 Gaithersburg, MD 20899, USA

^bNational Institute of Standards and Technology, 100 Bureau Drive, MS 8260 Gaithersburg, MD 20899, USA

Abstract

Manufacturing systems are becoming increasingly complex as more advanced and emerging technologies are integrated into the factory floor to yield new processes or increase the efficiency of existing processes. As greater complexity is formed across the factory, new relationships are often generated that can lead to advanced capabilities, yet produce unforeseen faults and failures. Industrial robot arm work cells within the manufacturing environment present increasing complexity, emergent technologies, new relationships, and unpredicted faults/failures. To maintain required levels of productivity, process quality, and asset availability, manufacturers must reconcile this complexity to understand how the health degradation of constituent physical elements and functional tasks impact one another through the monitoring of critical informative measures and metrics. This article presents the initial efforts in developing a novel hierarchical decomposition methodology. The innovation in this method is that it provides the manufacturer with sufficient discretion to physically deconstruct their system and functionally decompose their process to user-defined levels based upon desired monitoring, maintenance, and control levels. This enables the manufacturer to specify relationships within and across the physical, functional, and information domains to identify impactful health degradations without having to know all possible failure modes. The hierarchical decomposition methodology will advance the state of the art in terms of improving machine health by highlighting how health degradations propagate through the relationship network prior to a piece of equipment compromising the productivity or quality of a process. The first two steps of the methodology, physical decomposition and functional decomposition, are defined in detail and applied to a multi-robot work cell use case.

Keywords

Control; Diagnostics; Maintenance; Manufacturing process; Monitoring; Prognostics; Robotics; Smart Manufacturing

*Corresponding author. brian.weiss@nist.gov (B.A. Weiss).

1. Introduction

Manufacturing processes, and the corresponding physical systems that enable them, can be complex. This complexity has grown substantially due to the integration of advanced technologies and reconfigurable systems. Maintaining a factory's operational efficiency requires clear maintenance and control strategies [1,2]. Manufacturers are turning towards Smart Manufacturing (or Industry 4.0) practices to support these strategies [3–5]. Smart Manufacturing aims to integrate hardware, software, and data to increase operational efficiency, asset availability, and quality while lowering scrap and unscheduled downtime. Successful integration of these elements and acceptable, continued operational performance of the resultant system should provide manufacturers with the intelligence to minimize unscheduled process and equipment downtime; and flexibility to meet changing consumer demand and supply chain volatility.

The manufacturing evolution is being advanced by emergent, disruptive technologies (i.e., additive processes, collaborative robotic systems) and an abundance of more affordable sensing and visualization technologies [6]. Greater sensing, monitoring, and control capabilities have supported the development of new approaches to better manage complex manufacturing systems. For example, some of these approaches leverage energy consumption and efficiency metrics to promote smarter maintenance and control strategies across diverse platforms from the manufacturing floor down to machine tools and robot systems [7–9].

Complexity can be readily viewed in many robot systems that are currently operating on factory floors. Robot systems can be configured to perform numerous tasks in many manufacturing environments including aerospace [10–12], automotive [13–15], consumer packaged goods [16], and electronics [17,18]. Smart Manufacturing is elevating the capabilities of these robot systems through the integration of diverse end-effectors, sensors, and supporting automation (e.g., conveyor systems, linear rails) in concert with advanced data analytics and information visualization tools. In turn, these robot systems are becoming more adept to complete a range of tasks under changing conditions and parameters. These additional features and capabilities lead to increased complexity at the system, sub-system, component, etc. level of the overall work cell.

Another result of the added complexities is an increased potential for elements within the process or the system to experience faults or failures. Faults and failures typically create asset downtime leading to lost productivity and increased maintenance which leads to increased costs and decreased profits. Currently, the manufacturing community ranges from taking a 'react and repair' approach to taking a 'predict and prevent' approach to their maintenance [2,19]. Most manufacturers practice a combination of 'react, repair, and prevent' which is usually driven by a documented maintenance plan (the quality of documentation varies across the manufacturing community). Some innovative manufacturers are taking a 'predict and prevent' approach, yet they still succumb to 'react and repair' when faced with unexpected failures, albeit these unexpected failures are usually reduced in frequency and/or severity.

Manufacturers can only survive for so long on a strict ‘react and repair’ approach, especially if competition emerges and takes a ‘predict and prevent’ approach to process and equipment health. ‘React and repair’ typically involves greater maintenance costs (both in labor and materials) and has a more substantial impact on production since reactive maintenance is unplanned where both have a negative impact on costs and profits [2,3,19]. A benefit of adopting a ‘predict and prevent’ approach is that it will support evolving manufacturing process configurations as new technologies are integrated on the factory floor.

In addition to the intricacy presented by robot systems on the factory floor, other key technologies exist within manufacturing that increase complexity. Machine tools and additive manufacturing are two such technologies that are inherently complex. These technologies are currently being integrated with robot systems (e.g., industrial robot arms being used in machine tending operations) thereby creating greater complexity [20]. This complexity manifests itself as many relationships between a system’s physical elements, functional tasks, and the metrics/measures necessary to characterize system performance and health. Manufacturers are challenged in accurately and appropriately defining these relationships to understand how equipment and process health degradation propagate through the manufacturing system; the manufacturing community would like to see the development of a means of defining and organizing these relationships to support the design and implementation of their maintenance strategies [4,6].

The U.S. National Institute of Standards and Technology (NIST) is performing research to support the manufacturing community in the design, deployment, verification, and validation of advanced monitoring, diagnostic, and prognostic (collectively known as Prognostics and Health Management (PHM)) technologies to enhance maintenance and control strategies [21]. One research effort in this area is the development of a hierarchical decomposition methodology that will enable manufacturers to articulate the relationships across and between physical elements, functional tasks, and the metrics/measures so a manufacturer can make informed and strategic decisions on where and what PHM technologies should be deployed in their manufacturing operations. The innovation in this method is that it provides the manufacturer with sufficient discretion to physically deconstruct their system and functionally decompose their process to user-defined levels based upon desired monitoring, maintenance, and control levels; and enables the manufacturer to develop relationships within and across the physical, functional, and information domains to identify impactful health degradations without having to know all possible failure modes. The hierarchical decomposition methodology will advance the state of the art in terms of improving machine health by highlighting how health degradations propagate through the relationship network prior to a piece of equipment compromising the productivity or quality of a process. This paper presents the latest efforts in developing this methodology. Section 2 presents background on this effort including PHM within manufacturing. Section 3 discusses the hierarchical decomposition methodology. Section 4 details the initial application of the methodology to an in-house multi-robot use case. Section 5 discusses the findings of this effort and the next steps in developing the hierarchical decomposition methodology. Finally, Section 6 concludes the paper.

2. Background

2.1. Manufacturing work cells

Work cells are a critical unit of factory operations. These units vary in terms of size, scope, hardware, and software necessary to enable a cell's operation. Collectively, work cells are capable of many operations including welding, stamping, assembling, and machining [22–24]. These operations are enabled by a combination of industrial robot systems (e.g., robot arms, automatic/automated ground vehicles), machine tools, 3D-printers, and other automation (e.g., conveyor systems, linear rails) working together to turn raw material (or a part) into a part (or a more finished part).

Work cells present multiple layers of complexity to the overall manufacturing enterprise. They have their inherent complexity in that they can be construed as their own systems made up of subsystems, and components that work together to yield a process. Likewise, work cells may also be elements of the larger process occurring within a factory; the health of work cell elements influence both the health of the overall work cell and the higher-level systems in which the work cell is connected. Work cell health also influences the quality of its output parts. In turn, compromised part quality from a work cell can impact the health of higher-level systems and/or work cells downstream in the manufacturing process. Overall, this complexity makes it more difficult to ensure that a work cell's health is not compromised to the point where its availability, productivity, and quality (of the work cell-enabled process and/or output part) are not impacted. All three of these elements form the universal metric of Overall Equipment Effectiveness (OEE); a metric in which many manufacturers assess their operations [25]. A negative impact on any of OEE's constituent measures (availability, productivity, quality) will typically call a manufacturer to action; manufacturers are thus adopting PHM technologies to minimize (ideally, avoid) negative events.

2.2. Prognostics and health management

PHM refers to the field of monitoring, diagnostics, and prognostics aimed at enhancing maintenance and/or control strategies [26]. PHM has been applied to monitor, diagnose, and predict faults and failures in products across numerous industries including automotive, defense, earth-moving, and electronics [27–30]. PHM enhances maintenance and control by offering greater intelligence and awareness of the health of the specific process or product. To varying extents, PHM supports the numerous maintenance strategies available [2,3]:

- **Reactive maintenance** – unplanned repairs and maintenance are required after an unexpected fault or failure. Reactive maintenance is usually the least preferred maintenance strategy given that there is no opportunity to schedule asset downtime (given the unexpected fault/failure) and production will be impacted. Maintenance costs may also be relatively high if required parts are not in stock or specific personnel are required for the repair. Likewise, asset downtime could be relatively long if the required part(s) or maintenance personnel are not immediately available. Reactive maintenance is rarely preferred given its high likelihood to increase maintenance costs and reduce profits.

- Preventative maintenance – maintenance activities are scheduled at predetermined intervals (e.g., units produced, hours of production, cycles). Nearly every manufacturer practices some form of preventative maintenance on their processes and equipment. Preventative maintenance is usually driven by Original Equipment Manufacturer (OEM) recommended practices, lessons learned from past activities, or after determining that this type of maintenance is a more cost-effective approach than using another maintenance strategy. Asset downtime is usually controllable in this strategy and scheduled to minimally disrupt production (as much as reasonably possible).
- Predictive maintenance – maintenance activities are scheduled based upon gathered data and intelligence. Maintenance intervals will vary based upon changing operational parameters and process/equipment health. Available data and intelligence can allow manufacturers to schedule maintenance activities to minimally disrupt their production and minimize maintenance costs (e.g., if a failure is going to occur in 2 h, schedule maintenance before the failure (if optimal) or begin preparations to perform maintenance immediately upon failure, minimizing downtime).
- Proactive maintenance – certain maintenance activities are automatically conducted, without human intervention, to correct degraded health. Or this maintenance type could refer to certain control strategies being automatically adjusted to push back the time to failure so that human-driven maintenance activities may be scheduled to minimally disrupt production. This strategy is the most technologically complex to date, yet least-developed and rarely implemented within the manufacturing industry.

The advancement and implementation of PHM has led to the development of many PHM-based standards that have been adopted across many industries including the aerospace, automotive, and manufacturing domains [31,32]. It is worth noting that SAE International¹ is actively developing a suite of PHM standards within its HM-1 Integrated Vehicle Health Management Committee. These standards are expected to benefit both the aerospace and automotive communities. Some of the output standards have been adopted by regulatory agencies (e.g., the Federal Aviation Association adopting SAE International standards for aircraft maintenance) while others remain voluntary.

2.3. Manufacturing PHM

The implementation of strategic and structured PHM practices and techniques is largely a voluntary decision within the manufacturing community. To date, numerous end-users, technology integrators, technology developers, researchers, and standards development organizations have both provided critical input into manufacturing PHM requirements and developed a range of implementations [17,18]. There are numerous PHM approaches currently applied in manufacturing. These approaches can be characterized as physical model-based (i.e., physics-based), knowledge-based, data-driven, or hybrid (a combination

¹<https://www.sae.org/>.

of the three approaches) [33]. PHM approaches are being developed and applied to a large cross-section of manufacturing technologies including robot systems [17,34], linear axis/ball screw technologies [35,36], rotational machinery [37], and machine tools [38,39]. PHM deployment, and corresponding lessons learned, has been documented extensively within the manufacturing industry, yet challenges remain, especially with respect to independently verifying and validating emerging PHM solutions.

2.4. NIST research to advance the technology

NIST's *Prognostics, Health Management, and Control* (PHMC) project is specifically focused on developing measurement science for robust sensing, diagnostics, prognostics, and control that enable manufacturers to respond to planned and un-planned performance change thereby enhancing the efficiency of smart manufacturing systems [40,41]. This research effort is heavily influenced by manufacturing stakeholders including technology developers (both hardware and software), technology integrators, end-users (typically, the manufacturers, themselves), academic institutions and government organizations [4,21]. This research encompasses three levels within the manufacturing hierarchy [42]:

- System Level – Manufacturing Process and Equipment Monitoring [43,44]
- Work Cell Level – Health and Control Management of Robot Systems [34,42,45]
- Component Level – Machine Tool Linear Axes Diagnostics and Prognostics [46,47]

NIST not only structures its efforts in a hierarchical fashion, it also has a research focus to develop a hierarchical decomposition methodology to provide the manufacturing community with a tool that allows for the development of customized (not bound to a specific number of levels) hierarchy to promote the understanding of relationships across the physical, functional, and information domains. Before presenting the hierarchical decomposition methodology, some of the key hierarchical development activities within the manufacturing community are presented.

3. Hierarchical decomposition methodology

3.1. Motivation

The hierarchical nature of the PHMC research highlights the importance of relating influences of one level to another in terms of process/equipment degradation. How do changes at one level of the hierarchy impact lower-level and higher-level operations? Likewise, how do these changes influence other elements, at the same level, as information or parts flow 'downstream?' An approach that will guide manufacturers in where, what, when, and how to deploy PHM technologies within their manufacturing operations needs to be developed.

The hierarchical nature of the manufacturing environment is well-documented in the ANSI/ISA-95 standard "Enterprise – Control System Integration" [48]. This global standard promotes the development of an automated interface between an enterprise and its lower-level control systems. It is intended to be applied to all industries and processes within the

manufacturing community. Fig. 1 presents the standard's functional hierarchy that defines five levels – Level 0 through Level 4—that specify different functions and activities across different time horizons. The standard defines activities at each level and calls out maintenance operations management at Level 3, yet does not promote the insertion of additional levels, as desired, for health monitoring and maintenance.

Hierarchical decomposition methods and procedures have been developed and studied to yield a range of results varying in comprehension and value. NASA developed the Systems Engineering Handbook to promote the comprehensive design and assessment of new technologies through system and sub-system decomposition [49]. The systems engineering process is further supported by the “V” Model that steps through the system decomposition in design and the ‘build up’ during the evaluation processes [50].

The manufacturing community has also developed numerous methods that are employed to determine ways a product or process can fail. One of the more common methods is Failure Modes and Effects Analysis (FMEA) which is a documented step-wise process to identify as many failures as possible in a design, manufacturing process, or product [51,52]. A successful FMEA requires the user to identify potential failure modes which usually requires historical knowledge of similar systems or sub-systems. The development of FMEA has spawned several related methods – Failure Modes and Effects Criticality Analysis (FMECA) and Process Failure Modes and Effects Analysis (PFMEA) [53–55]. The methods have proven effective in aiding a process or product designer in determining how they can mitigate the risk of a failure. However, these methods don't focus on the relationships between physical elements, functional tasks, and informational metrics across the multiple levels of the hierarchy to highlight degradation to predict where and when faults or failures may occur.

NIST is developing a hierarchical decomposition methodology to be a cost-effective, methodical approach to guide manufacturers through the PHM design and deployment process when all of the failure modes are not known. The methodology would specifically address the following questions that plague manufacturers:

- What physical or task degradation has the potential to impact performance metrics that are most critical within a process?
- What data, leading to intelligence, is needed about the process to determine where and when health degradation will occur?
- How should the risk of faults and failures be prioritized in the system and process?
- How does the health of the physical system, and its constituent elements, influence the health of the process?

This effort is important given both the shortcomings of existing methods in industry and manufacturer feedback captured from a recent *Workshop on Advanced Monitoring, Diagnostics, and Prognostics* [6]. Some of the industry feedback highlighted the importance of developing guidance to help manufacturers in determining what data to capture, what data collection strategies they should employ, and what and where sensors should be deployed to

inform on process/equipment health. The hierarchical decomposition enables the development of this specifically-requested guidance.

A hierarchical modeling scheme has the potential to summarize and refine complex relationships in an easy to discern manner that is both efficient and understandable by users not versed in the underlying complexities of the physical or cyber-physical system. By linking separate models, each designed to provide a health indication of some sub-level of a higher-level system, the subsequent higher-level model can more easily extract the most important information pertaining to that higher-level system's total health. By monitoring a set of interconnected lower-level systems as a group, (via the higher-level model) instances of false alerts due to common issues can be identified. Ideally, this can lead to the identification of the true root cause, but in less than ideal cases, it can reduce the number of false alarms and provide tangible benefits to the end user. Reducing false alarms lowers the time needed to trace faults, reduces maintenance or investigative action needs, and generally adds more weight and perceived importance to the alarms that get presented to the user.

Managing and constructing a higher-level model to reflect and monitor the relationships between linked lower-level models can come in various forms. The more traditional, but often less broadly applicable, are those models that have direct, physics-based relationships. Where applicable, these can provide easily interpreted, intuitive results. Unfortunately, the exact parameterization of these model styles is difficult to determine for a specific system or set of systems, and can have negative effects on model performance if not properly constructed. Both expert knowledge of the type of system being modeled and, in many cases, intimate knowledge of the specific instance of the system including sensor placement and specifications, are needed to construct many physics-based models. A simple example of these types of models could be an electric motor driving a gearbox. To correctly identify anomalous vibrations, both the motor and the gearbox should be monitored, with explicit knowledge of rotation speeds, gear ratios, interactions, and any attenuation due to sensor placement. This level of expertise could provide a cost barrier for wide implementation.

Another method for modeling these types of systems could be data driven approaches such as Artificial Intelligence, machine learning, empirical modeling, or other non-parametric information inferences. Modeling methods such as these have the distinct advantage of being widely applicable with little expertise about the actual system being modeled. A significant drawback is that the less explicit information incorporated into this style of model during construction, the more extensive the data requirements for training these models. These types of models excel at capturing subtle relationships between inputs that the original designer may not even be aware. Unfortunately, this occasionally leads to the indication of anomalous behavior (e.g., from health degradation, changing performance) within the system that may not have an easily identifiable source. Hybridizations of both data driven techniques and physics-based approaches can be used to mitigate these kinds of occurrences while leveraging the strengths of both. The suggested hierarchical modeling can inherently provide a basis for hybridizations. As the linking of models follows the physical and cyber-physical relations of a set of subsystems, this designates the physics-based relationships even where the explicit analytic form of those relations may not be known. In those cases, a generic function mapping model, such as a neural network, could be employed to implicitly

model and monitor the relationships between the subsystems, and allowing for a degree of physical interpretation of higher-level alerts by tracing it to lower level models.

3.2. Methodology definition

The hierarchical decomposition methodology is highlighted in the flow diagram presented in Fig. 2. The process can be decomposed into eight primary steps. To date, the overall process is outlined and the first two steps are presented in additional detail. The remaining steps will be detailed in future work and may draw upon some best practices of existing methods documented in Section 3.1. Section 4 applies the initial steps of this process to an in-house robot work cell.

3.2.1. Step 1—physical decomposition—The first step is to break down the physical work cell into its building block sub-systems, components, sub-components, etc. based upon user-defined boundaries (Note – depending upon how the user breaks down their system, there could be deeper levels beyond sub-components). The manufacturer/user defines the levels of their system (i.e., the work cell, sub-systems within the work cell) based upon their *Maintenance, Monitoring, and Control Levels* (MMCLs) [56]. This translates into the levels that the manufacturer/user cares to monitor for performance or health degradations, the levels which maintenance is performed, and the levels in which are controlled during the manufacturing process. This step requires substantial input from the manufacturer based upon the sub-systems, components, and sub-components they will actively perform maintenance on vs. those physical elements they will simply monitor and have external personnel perform maintenance. Multiple personnel are likely to provide critical input into this step, in addition to the operator, themselves. It's also important to note that the operator, as someone who directly interacts with the work cell and can influence its health, should also be considered part of the system. For example, a manufacturer choosing to perform their own maintenance on their robot arm may want to do the physical decomposition such that motors, gears, and encoders are explicitly called out for each joint. Conversely, a manufacturer that prefers to pay an external organization to maintain their robot may simply decompose their system down to individual joints (groupings of motors, gears, and encoders), or stop a level higher up at the robot arm (inclusive of all joints). Completing this first step may take a substantial time commitment from the manufacturer (and/or an engaged external organization), especially during the first iteration of physically decomposing a system. Similar to predictive maintenance, this method requires an upfront investment to achieve savings later in the system's lifecycle. Thoughtfully and strategically decomposing a system will make it easier for a manufacturer to predict where a fault or failure will occur, how it will reveal itself before it negatively impacts OEE, and identify specific elements within the system that should receive maintenance.

The user defines the overall System, S_0 , and the first level (subsystem) elements underneath as shown in Definition (1). The first level may also be referred to as the sub-system level. Since the highest level only contains the overall system, this level is called the zero level.

$$S = \{S_1 \dots S_i\} \text{ for } 1 \text{ to } n. \quad (1)$$

where n = the total number of elements at the sub-system level.

Definition (2) and Definition (3) define the second level elements. The second level may also be defined as the component level.

$$S_1 = \{S_{11} \cdots S_{1a}\} \text{ for } 1 \text{ to } a. \quad (2)$$

where a = the number of elements at the component level under the first element of the sub-system level

$$S_n = \{\{S_{11} \cdots S_{1a}\}, \{S_{21} \cdots S_{2b}\} \cdots \{S_{n1} \cdots S_{nz}\}\} \quad (3)$$

where b = the number of elements at the component level under the second element of the sub-system level and z = the number of elements at the component level under the n^{th} element at the first level.

The second level elements would be broken down into third level elements, and so on, in a similar fashion, as necessary. The physical decomposition tree for the zero level, and subsequent first and second levels, is shown in Fig. 3.

The physical decomposition tree would extend as far down as necessary based upon the user-defined levels. This tree purely shows the breakdown of the physical system. What it does not show is the physical connections between the sub-systems and components. Fig. 4 presents the structure for how physical elements at the same level are connected. This figure stops at the sub-system level, yet the same structure can be applied at the component and lower levels. Solid lines between elements on the same level indicate a fixed connection throughout the manufacturing process (e.g., a controller would be connected to a robot arm throughout corresponding manufacturing operations). Dotted lines between elements at the same level indicate temporary or periodic connections throughout the manufacturing process (e.g., a gripper holds a part for a portion of the process but does not hold it for the entire process). It is possible that multiple, unique relationships may exist between two elements at the same level. For example, a gripper may grasp a part in two different positions to correspond to two unique operations that are being performed on that part during the manufacturing process.

3.2.2. Step 2—functional decomposition—Step 2 is to break down the process within the work cell into its constituent tasks, sub-tasks, etc. This decomposition should be driven by the control strategy, modularity of the tasks and sub-tasks for improvement or reconfiguration, and what is deemed critical to monitor. This step is also heavily human-driven. The highest level of the functional decomposition is the zero level and represents the overall process, P , as defined in Definition (4).

$$P = \{P_1 \cdots P_i\} \text{ for } 1 \text{ to } m. \quad (4)$$

where m = the total number of tasks at the first level

$$P_1 = \{P_{11} \cdots P_{1c}\} \text{ for } 1 \text{ to } c. \quad (5)$$

where c = the number of sub-tasks at the second level under the first task of the first level

$$P_m = \left\{ \{P_{11} \cdots P_{1c}\}, \{P_{21} \cdots P_{2d}\} \cdots \{P_{m1} \cdots P_{my}\} \right\} \quad (6)$$

where d = the number of sub-tasks at the second level under the second task of the first level
and y = the number of sub-tasks at the second level under the m^{th} task at the first level.

Fig. 5 presents the functional decomposition tree, similar to the physical decomposition tree in Fig. 3. The structure governing the visual representation of task to task and sub-task to sub-task connections is similar to what is presented in Fig. 4; solid arrows represent task (or sub-task) flow that is constant throughout the manufacturing operation (e.g., task 1 is always followed by task 2) and broken arrows represent task (or sub-task) flow that could vary (e.g., task 1 is either followed by task 2 or task 3). In this example, there would be broken lines drawn between tasks 1 and 2, and tasks 1 and 3).

3.2.3. Step 3—process and task metric identification—The third step is to identify all metrics that are captured (or should be captured if the work cell in question is a new manufacturing system still in its design stages) at the process, task, and sub-task levels. This step begins at the highest level of the process by identifying the metrics that represent the health of the process (not of the physical equipment). It is common for manufacturers to report OEE from multiple levels within their factory including OEE across the entire factory, OEE of an assembly, and OEE of a work cell. The building block metrics of OEE contain information that manufacturers care about: productivity (e.g., cycles/unit time), quality (e.g., accuracy of output parts), and availability (e.g., percentage the process is operational across a larger timescale). Productivity is relevant to the functional domain as it reports on the process. Availability is relevant to the physical domain as it traces back to machine health. Quality can be traceable back to both the physical domain as it can inform upon the part as impacted by a specific piece of equipment, and functional domain as it can inform upon process health. Any negative change in these metrics impacts the manufacturer's ability to meet its production targets or needed quality specifications. These process metrics are then broken down further into their constituent metrics. Likewise, the critical metrics representing the health of individual tasks, and sub-tasks, defined in Step 2, are identified. It is likely these task- and sub-task-level metrics overlap with the metrics captured from the breakdown of the process metrics. Any metrics, that appeared during the process metric breakdown, yet did not show up in the task- and sub-task-level metric identification should be scrutinized. This could indicate that a task or sub-task was missed in Step 2. Before moving to Step 4, the first three steps should be iterated to ensure sufficient and appropriate coverage is attained.

3.2.4. Step 4—risk identification—Step 4 is to identify the sources of risk within the work cell. This step is guided by knowledge of what has faulted or failed in the past, what could theoretically fault or fail, the likelihood a fault or failure will occur, and the expected impact of a realized fault or failure. Future efforts will articulate this step including how the user should proceed if they can only capture linguistic likelihood (e.g., very unlikely, unlikely, etc.) or impact (e.g., negligible, minor, etc.) information as opposed to quantitative likelihood (e.g., <0.1%, <0.5%, <1%, etc.) or impact (e.g., hours of downtime, monetary cost); at what level(s) this is done (physical vs. functional level vs. both levels); and how risk should be aggregated. An initial completion of this step is also expected to lead to reiterating upon the first three steps, if the levels of decomposition need to be further expanded or consolidated, or if additional process metrics need to be considered. The development of this step will be further supported with a deeper exploration into the FMEA family of methods. These methods include an element of risk identification that may prove valuable to the hierarchical decomposition methodology. Likewise, fuzzy logic will also be examined given its past use in risk assessment [57,58].

3.2.5. Step 5—risk reduction—Step 5 involves considering options that would lower the risk of faults and failures. Reductions can occur in five different ways as shown in Fig. 6. Consideration of these options should lead the user to select which option(s) is preferred (optimal, ideally) to reduce risk.

Each of the options presented in Fig. 6 are also detailed below.

- a. Elimination – the process is altered or the physical equipment is eliminated to remove the mode of fault or failure, altogether.
- b. Substitution – the process is altered or different physical equipment is used to lessen the risk of fault or failure or add a lesser risk while removing the greater risk.
- c. Proactive Maintenance Automation – sensors, technology, and intelligence are added to automatically respond to impending faults or failures to minimize impacts on production and quality. This may involve a dynamic control or limited maintenance strategy until the necessary maintenance can be performed. A human only interacts with the system when more thorough maintenance is warranted/needed.
- d. Predictive Maintenance Manual Implementation – human situational awareness, possibly coupled with sensors and technology, track the health of the process or equipment where the human operator/manufacturer determines when maintenance will be performed.
- e. Preventative/Reactive Maintenance Implementation – this is sometimes the least preferred means of risk reduction. To lessen the potential for a fault or failure, maintenance routines are performed at discrete intervals (e.g., hours, cycles). If a fault or failure is realized, reactive maintenance is performed to restore the process to a functioning state. Reactive maintenance can be viewed as risk

reduction when the goal is to restore equipment/process health to prevent a chain reaction of additional faults or failures from occurring.

3.2.6. Step 6—data collection—Step 6 is to determine the critical data for collection and identify the best collection approach (e.g., sensor selection, sensor location, frequency of data capture). A manufacturer's desired strategy will be influenced by numerous factors including exigent risk and available resources. This will be expanded upon in future efforts. At a high level, manufacturers differ in their risk profiles where large manufacturers are more likely to take greater risk to advance their technological capability since they usually have greater capital to invest, yet small to medium-sized manufacturers are more risk averse given their limited monetary and personnel resources.

3.2.7. Step 7—physical element metric identification—Step 7 is to determine the measures and metrics that can provide intelligence on physical system and its constituent component, and sub-component health. These measures and metrics are then mapped back to the process and task metrics defined in Step 3—Process and Task Metric Identification. It is important to note that the metrics identified in Step 3 are aimed at informing on the health of process (e.g., units per hour, takt time) while the metrics identified in Step 7 are informing on the health of physical elements (e.g., machine current, robot end-effector velocity).

Steps 5, 6, 7, and 8 are iterative. After completing Step 7, the user should revisit Steps 5 and 6 to determine if further risk reduction can be performed and the data collection strategy can be refined. Similarly, after completing Step 8, the user may want to go back to Steps 5, 6, and 7.

3.2.8. Step 8—relationship mapping and quantification—Step 8 is to map the connections across the physical, functional, and informational dimensions, and the connections within individual dimensions (both across higher and lower levels, and within the same level). This step documents the influence and impact that faults and failures can produce across the numerous levels and dimensions of the work cell. The output of Step 8 will include relationship matrices to mathematically represent the connections in and across the physical, functional, and informational dimensions. It is expected that these matrices will document the varying levels of influence that the physical, functional, and informational dimensions have on one another, along with the levels of influence they have on their own constituent elements.

As mentioned earlier, steps three through eight are still in development or pending development. The following application section highlights steps one and two within the PHMC project's robot work cell. The third step will be briefly touched upon as it is still in process. Additional steps will be discussed in future work.

4. Application to in-house robot work cell

A manufacturing robot work cell use case is designed and built to support the PHMC project's measurement science efforts [41,42]. The use case built for the robotics test bed is

a multi-robot work cell which performs industrially-relevant processes (shown in Fig. 7). One industrial robot arm, equipped with a parallel gripper end effector, performs material handling tasks, moving parts from an input to a work fixture, and from the work fixture to an output. These pick-and-place tasks are often found in applications such as machine tending, palletizing, and other product transport-related operations. The second robot, equipped with a compliant pen-holding end effector, draws on the parts. This task is representative of trajectory-controlled motions where robot pose (position and orientation) throughout its operation is critical to success within applications such as welding, dispensing (e.g., ejecting glue), and 3D printing. The work cell process is managed and controlled by a programmable logic controller (PLC). The PLC also serves as a data aggregator and real-time processor, capable of monitoring robot data (e.g., joint positions and system status), and other data sources within the work cell for use in PHM technology implementations. The test bed provides a platform to artificially induce real or simulated degradations to verify and validate PHM implementations.

From the part perspective, the use case can be broken down into three main steps: 1) an unfinished part is moved from the input to a work fixture by the material handling robot; 2) the NIST logo is drawn on the part by the drawing robot, finishing the part; 3) the finished part is moved from the work fixture to the output bin by the material handling robot. Loading unfinished parts at the input and removing finished parts from the output are manual processes which could be automated in the future.

4.1. Physical decomposition

Fig. 8 presents the system and sub-system level physical decomposition of the multi-robot work cell that serves as the PHMC use case. The component and sub-component level decomposition is limited due to space limitations.

This physical decomposition in Fig. 8 presents the fixed, physical relationships between the safety systems, PLC, drawing robot and the material handling robot with solid lines. Additionally, periodic relationships are shown between both robots and the part (being operated upon), and the part with the input tray, work fixture, and output bin with dotted lines. These periodic relationships change throughout the manufacturing operation as parts flow through the process (discussed in detail in Section 4.2). Each of the two robots is broken down into three constituent components, respectively, including their robot arms, controllers, and end-effectors (only the deeper relationships of the Material Handling Robot are shown in Fig. 8 due to space limitations). Furthermore, each of the robot arms is broken down into their six constituent joints. These robot joints represent the sub-component level. These deeper levels of decomposition and corresponding variable identifiers are shown in Table 1.

As noted, only the robot sub-systems and constituent robot arm components are broken down to lower levels. Given the influence that the robot's health has on the overall productivity and quality of the manufacturing process, it's typical for manufacturers to monitor health and performance down to these levels, though not all manufacturers choose to do so. Of course, the hierarchical decomposition methodology gives the manufacturer the

discretion to break down their physical system to levels that support their specific monitoring, maintenance, and control desires.

4.2. Functional decomposition

The functional decomposition tree is developed for the PHMC manufacturing use case and is partially shown in Fig. 9. The work cell process is broken down into three distinct and sequential tasks: Move a part to the work fixture, draw the NIST logo on the fixtured part, and place the completed part in the output bin. Each of these three tasks is broken down into sub-tasks, also shown in Fig. 9.

The division of tasks and sub-tasks is based upon the control strategy that is employed and at the manufacturer's discretion. In manufacturing systems, some tasks and sub-tasks could occur in parallel, making the functional decomposition look very different. At this stage of the test bed work cell's development, the subtasks are not broken out further. As the work cell matures and additional complexity is added, it is expected that the functional decomposition will evolve to include additional tasks, sub-tasks, and/or additional levels (beyond the sub-task level).

5. Discussion and next steps

Steps 1 and 2, the physical and functional decompositions of the system and process, respectively, are important foundational steps in building up the hierarchical decomposition methodology. The next steps, including the identification of process and task metrics (Step 3), will be directly linked back to the functional decomposition to reinforce the existing functional structure or influence it to evolve to be more representative of what the manufacturer finds most critical in terms of monitoring, maintenance, and control levels. It is likely that the identification of process and task metrics will begin with an examination of OEE given this represents information that many manufacturers value.

An important part of both the physical and functional decompositions are the relationships within the respective hierarchies. Fig. 8 presented the constant and periodic relationships among physical elements showing all physical relationships in the work cell are not equal. Some physical relationships will have more substantial impact on the overall performance and health of the work cell compared to other relationships (e.g., a tool bit wears differently if it is cutting steel as compared to aluminum). This will be explored in future work. Similarly, Fig. 9 presented the sequence of tasks and sub-tasks. Tasks (and sub-tasks) that occur in series are likely to have different relationships than tasks that occur in parallel. Relationship matrices, both in the physical and functional domains, will be developed to further articulate the nature of these influential relationships. The relationship matrices, coupled with the definition of elements at the multiple levels of the physical and functional hierarchies will enable, will support risk identification and propagation for the work cell in Step 4.

Overall, the hierarchical decomposition methodology is envisioned to be a valuable tool to the manufacturing community by providing a consistent and comprehensive process to design monitoring, diagnostic, and prognostic technology implementations on the factory

floor. Physical and functional decompositions, especially in determining how far down the hierarchies to go and how elements within a domain interact with one another, are both nontrivial and discretionary.

Near term efforts are focused on developing Step 3 (Process and Task Metric Identification) and Step 4 (Risk Identification). In parallel with this effort, metrics are actively being defined that can be used to articulate Step 3 in an example. The declaration of use case metrics will also be coupled with levels of importance to determining process performance and equipment health. These levels of importance are expected to be critical input for Step 3 and Step 4.

Once Step 3 and Step 4 are defined, work will continue to define the remaining steps of the hierarchical decomposition process. Preliminary pilot studies and implementations of this process will be performed on in-house NIST test beds. In addition to applying this to the PHM for Robot Systems test bed, two other test beds are being explored for application: a robotics enclave that includes two robots performing collaborative material handling operations and the NIST Smart Manufacturing Systems (SMS) test bed that features over ten heterogeneous machine tools networked together sharing performance and health data to support higher-level scheduling and maintenance activities. The physical, functional, and information hierarchies of the robotics enclave are relatively simple. Conversely, there is greater complexity across the NIST SMS. The addition of these two test beds can support further development, verification, and validation of the hierarchical decomposition methodology across robot systems, machine tools, and other automation systems. In parallel, preliminary implementations of the methodology within actual manufacturing environments will be explored with external partners. Of the external partners identified to date, the one who will likely support an early pilot implementation is an active manufacturer that operates over 100 machine tools including a heterogeneous mix of boring machines, vertical machine centers, horizontal machining centers, and grinders. This real-world implementation is expected to provide valuable feedback regarding the ease of the method's implementation and the value it brings to the manufacturer including the hierarchical levels within the factory (or machine center) the manufacturer is most concerned (and therefore defines). This feedback will prompt improvements and iterations to strengthen the method's capability.

6. Conclusions

The first two steps of the hierarchical decomposition methodology have been developed and applied to the NIST PHMC multi-robot use case. This effort provides the foundation for building the remainder of the methodology to provide the manufacturing community with a tool that will provide specific guidance with respect to identifying and implementing appropriate levels of monitoring, diagnostic, and prognostic technologies at the factory floor to enhance maintenance and control strategies. This methodology is novel in both the way it allows the user to specify how deep they want to decompose their physical and functional hierarchies; and how the methodology will ultimately allow a manufacturer to identify precursors to failure through relationship mapping without knowing all possible failures. To date, the manufacturing community has provided feedback on the concept and initial development of this work where value is seen in furthering its development and ultimately

implementing it on real factory floors. Specific conversations with numerous manufacturers have revealed that the proposed structure of the hierarchical decomposition methodology would provide a uniform process with which a manufacturer can strategically and efficiently deconstruct its system. This would offer a greater awareness of how both faults and failures ripple throughout a system, and identify key relationships allowing process and equipment metrics to identify impending faults and failures well before they negatively impact manufacturing operations.

7. NIST disclaimer

The views and opinions expressed herein do not necessarily state or reflect those of NIST. Certain commercial entities, equipment, or materials may be identified in this document to illustrate a point or concept. Such identification is not intended to imply recommendation or endorsement by NIST, nor is it intended to imply that the entities, materials, or equipment are necessarily the best available for the purpose.

Biographies

Dr. Brian A. Weiss is a mechanical engineer and the project leader at the NIST. His current efforts are focused on developing measurement science to verify and validate emerging monitoring, diagnostic, and prognostic technologies and strategies for smart manufacturing to enable manufacturers to respond to planned and un-planned performance changes. Prior to his manufacturing research, he spent 15 years conducting performance assessments across military and first response technologies including autonomous ground vehicles; tactical applications on Android™ devices; advanced soldier sensor technologies; free-form, speech-to-speech translation devices for tactical use; urban search and rescue robots; and bomb disposal robots. His efforts have earned him numerous awards including a Department of Commerce Gold Medal, Colleague's Choice Award, Silver Medal, two Bronze Medals, and the Rabinow Applied Research Award. He has a B.S. in Mechanical Engineering, Professional Masters in Engineering, and Ph.D. in Mechanical Engineering from the University of Maryland, College Park, Maryland, USA.

Dr. Michael E. Sharp is a Reliability Engineer at the National Institute of Standards and Technology (NIST) located in Gaithersburg, MD. He received a B.S (2007), M.S. (2009), and Ph.D. (2012) in Nuclear Engineering from the University of Tennessee, Knoxville, TN, USA. His research interests include signal analytics, machine learning, artificial intelligence, optimization, and natural language processing. Michael has worked on a wide array of projects including image processing for elemental material recognition, prognostics for electric motors undergoing transient operations, and control systems for deep space reactors. He currently works with the NIST Systems Integration Division for Smart manufacturing.

Alexander Klinger has a B.S. in Mechanical Engineering (2013) from Lehigh University, Bethlehem, Pennsylvania and a Masters of Engineering in Mechanical Engineering (2017) from the University of Maryland, College Park, Maryland. He is currently a mechanical engineer working on the Prognostics, Health Management and Control project within the Engineering Laboratory (EL) at the National Institute of Standards and Technology (NIST)

focusing on PHM for industrial robot systems. Prior to his role at NIST, he was a mechanical engineer at the United States Postal Service (USPS) Engineering Headquarters, working on automation and robotic systems.

References

1. Lee J, Ghaffari M, Elmeligy S. Self-maintenance and engineering immune systems: towards smarter machines and manufacturing systems. *Annu Rev Control*. 2011; 35(1):111–22.
2. Jin X, Siegel D, Weiss BA, Gamel E, Wang W, Lee J, et al. The present status and future growth of maintenance in US manufacturing: results from a pilot survey. *Manuf Rev*. 2016; 3:10.
3. Jin X, Weiss BA, Siegel D, Lee J. Present status and future growth of advanced maintenance technology and strategy in US manufacturing. *Int J Prognostics Health Manage*. 2016; 7(Sp5):18.
4. Weiss, BA, Vogl, GW, Helu, M, Qiao, G, Pellegrino, J, Justiniano, M. , et al. Measurement science for prognostics and health management for smart manufacturing systems: key findings from a roadmapping workshop, annual conference of the prognostics and health management society 2015. Society, P, editor. 2015. 11
5. Kagermann, H, Helbig, J, Hellinger, A, Wahlster, W. Recommendations for implementing the strategic initiative INDUSTRIE 4.0: securing the future of German manufacturing industry. 2013. Final report of the Industrie 4.0 Working Group, Forschungsunion
6. Weiss BA, Alonzo D, Weinman SD. Summary report on a workshop on advanced monitoring, diagnostics, and prognostics for manufacturing operations. 2017
7. Palasciano C, Bustillo A, Fantini P, Taisch M. A new approach for machine's management: from machine's signal acquisition to energy indexes. *J Clean Prod*. 2016; 137:1503–15.
8. Paes K, Dewulf W, Elst KV, Kellens K, Slaets P. Energy efficient trajectories for an industrial ABB robot. *Procedia CIRP*. 2014; 15:105–10.
9. Bhinge R, Park J, Law KH, Dornfeld DA, Helu M, Rachuri S. Toward a generalized energy prediction model for machine tools. *J Manuf Sci Eng*. 2017; 139(4):041013. [PubMed: 28652687]
10. DeVlieg R. Expanding the use of robotics in airframe assembly via accurate robot technology. *SAE Int J Aerosp*. 2010; 3(1):198–203.
11. Jeffries KA. Enhanced robotic automated fiber placement with accurate robot technology and modular fiber placement head. *SAE Int J Aerosp*. 2013; 6(2):774–9.
12. Summers M. Robot capability test and development of industrial robot positioning system for the aerospace industry. *SAE Trans*. 2005; 114(1):1108–18.
13. Kahan T, Bukchin Y, Menassa R, Ben-Gal I. Backup strategy for robots' failures in an automotive assembly system. *Int J Prod Econ*. 2009; 120(2):315–26.
14. Kusuda Y. Robotization in the Japanese automotive industry. *Ind Rob*. 1999; 26(5):358–60.
15. Wilson M. Vision systems in the automotive industry. *Ind Rob*. 1999; 26(5):354–7.
16. Zwicker, C, Reinhart, G. Human-robot-collaboration system for a universal packaging cell for heavy electronic consumer goods In: Enabling manufacturing competitiveness and economic sustainability. Springer; 2014. 195–9.
17. Edinbarough I, Balderas R, Bose S. A vision and robot based on-line inspection monitoring system for electronic manufacturing. *Comput Industry*. 2005; 56(8–9):986–96.
18. Malheiros P, Costa P, Moreira AP, Ferreira M. Ieee Robust and real-time teaching of industrial robots for mass customisation manufacturing using stereoscopic vision, Iecon: 2009 35th annual conference of Ieee industrial electronics. 2009; 1–6:2205–10.
19. Helu M, Weiss BA. The current state of sensing, health management, and control for small-to-medium-sized manufacturers. *Proc ASME 2016 manufacturing science and engineering conference, MSEC 2016*. 2016
20. Rooks B. Machine tending in the modern age. *Ind Rob: Int J*. 2003; 30(4):313–8.
21. Pellegrino, J, Justiniano, M, Raghunathan, A, Weiss, BA. Measurement science roadmap for prognostics and health management for smart manufacturing systems. 2016. NIST Advanced Manufacturing Series (AMS)

22. Xu X, Newman ST. Making CNC machine tools more open, interoperable and intelligent—a review of the technologies. *Comput Ind.* 2006; 57(2):141–52.
23. Ahmad R, Plapper P. Safe and automated assembly process using vision assisted robot manipulator. *Procedia CIRP.* 2016; 41:771–6.
24. Ogbemhe J, Mpofu K. Towards achieving a fully intelligent robotic arc welding: a review. *Ind Rob-Int J.* 2015; 42(5):475–84.
25. Liker JK. Is OEE a useful key performance indicator? *Industry Week.* 2014
26. Vogl, GW; Weiss, BA; Helu, M. A review of diagnostic and prognostic capabilities and best practices for manufacturing; *J Intell Manuf.* 2016. 1–17.
27. Fang H, Xiong Y, Luo K, Han L. The study of the helicopter rotor prognostic method and health management system based-on FMA. *Proc 2012 3rd annual IEEE prognostics and system health management conference, PHM-2012.* 2012
28. Camci F, Valentine GS, Navarra K. Methodologies for integration of PHM systems with maintenance data. *Proc 2007 IEEE aerospace conference.* 2018:4161674.
29. Holland SW, Barajas LG, Salman M, Zhang Y. PHM for automotive manufacturing & vehicle applications. *Proc prognostics & health management conference.* 2018
30. Line JK, Krishnan G. Managing and predicting intermittent failures within lone life electronics. *Proc 2008 IEEE aerospace conference, Inst of Elec and Elec Eng Computer Society.* 2008
31. Vogl, GW, Weiss, BA, Donmez, MA. Standards Related to Prognostics and Health Management (PHM) for manufacturing, No. NISTIR 8012. Gaithersburg, Maryland, USA: National Institute of Standards and Technology (NIST); 2014.
32. Vogl GW, Weiss BA, Donmez MA. Standards for prognostics and health management (PHM) techniques within manufacturing operations. *Proc annual conference of the prognostics and health management society.* 2014
33. Peng Y, Dong M, Zuo MJ. Current status of machine prognostics in condition-based maintenance: a review. *Int J Adv Manuf Technol.* 2010; 50(1–4):297–313.
34. Qiao G, Weiss BA. Accuracy degradation analysis for industrial robot systems. *ASME international manufacturing science and engineering conference.* 2017:9.
35. Vogl GW, Weiss BA, Donmez MA. A sensor-based method for diagnostics of machine tool linear axes. *annual conference of the prognostics and health management society,* 2015. 2015:1–10.
36. Jin W, Chen Y, Lee J. Methodology for ball screw component health assessment and failure analysis. *Proc ASME 2013 international manufacturing science and engineering conference collocated with the 41 st North American manufacturing research conference.* 2013:V002T002A031–V002T002A031.
37. Lee J, Wu F, Zhao W, Ghaffari M, Liao L, Siegel D. Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. *Mech Syst Signal Process.* 2014; 42(1):314–34.
38. Edrington B, Zhao B, Hansel A, Mori M, Fujishima M. Machine monitoring system based on MTConnect technology. *Proc 3rd international conference on through-life engineering services, TESConf.* 2014:92–7.
39. Vichare P, Nassehi A, Thompson J, Newman ST, Wood F, Kumar S. Machine tool capability profiles for representing machine tool health. *Rob Comput-Integr Manuf.* 2015; 34:70–8.
40. National Institute of Standards and Technology. Prognostics, health management, and control (PHMC). 2017. <http://www.nist.gov/el/isd/ks/phmc.cfm>
41. Weiss BA, Helu M, Vogl GW, Qiao G. Use case development to advanced monitoring, diagnostics, and prognostics in manufacturing operations. *IMS2016 – intelligent manufacturing systems.* 2016:6.
42. Weiss BA, Klinger AS. Identification of industrial robot arm work cell use cases and a test bed to promote monitoring, diagnostic, and prognostic technologies. *Proc 2017 annual conference of the prognostics and health management (PHM) society.* 2018:9.
43. Hedberg, T; Helu, M. Smart Manufacturing Systems (SMS) Test Bed. 2016. http://www.nist.gov/el/facilities_instruments/smstestbed.cfm

44. Helu M, Hedberg T. Enabling smart manufacturing research and development using a product lifecycle test bed. *Procedia Manuf.* 2015; 1:86–97. [PubMed: 28664167]
45. Qiao G, Schlenoff CI, Weiss BA. Quick positional health assessment for industrial robot prognostics and health management (PHM). *IEEE international conference on robotics and automation* 2017. 2017:6.
46. Vogl GW, Pavel R, Archenti A, Winnard TJ, Mennu MM, Weiss BA, et al. Identification of machine tool geometric performance using on-machine inertial measurements. *6th international conference on virtual machining process technology (VMPT 2017)*. 2017:6.
47. Vogl GW, Donmez MA, Archenti A, Weiss BA. Inertial measurement unit for on-Machine diagnostics of machine tool linear axes. *Annual conference of the prognostics and health management society* 2016. 2016:7.
48. International Society of Automation. *ANSI/ISA-95.00.01-2010–enterprise-control system integration-part 1: models and terminology*. 2010
49. Kapurch, SJ. *NASA systems engineering handbook*. DIANE Publishing; 2010.
50. Haskins C, Forsberg K, Krueger M, Walden D, Hamelin D. *Systems engineering handbook*. Proc INCOSE. 2018
51. Carlson, C. *Effective FMEAs: achieving safe, reliable, and economical products and processes using failure mode and effects analysis*. John Wiley & Sons; 2012.
52. International Electrotechnical Commission. *IEC 60812 – analysis techniques for system reliability –procedure for failure mode and effects analysis (FMEA)*. 2006
53. Bowles, JB. The new SAE FMECA standard proc. reliability and maintainability symposium; Proceedings, annual, IEEE. 1998. 48–53. <http://ieeexplore.ieee.org/abstract/document/653561/>
54. Lipol LS, Haq J. Risk analysis method: FMEA/FMECA in the organizations. *Int J Basic Appl Sci.* 2011; 11(5):74–82.
55. Mikosa WL, Ferreira JCE. Knowledge sharing and reuse in potential failure mode and effects analysis in the manufacturing and assembly processes (PFMEA) domain. *Complex Syst Concurr Eng.* 2007:461–8.
56. Weiss, BA, Qiao, G. *ASME 2017 International Manufacturing Science and Engineering Conference (MSEC2017)*. Los Angeles, California: ASME; 2017. Hierarchical Decomposition of a Manufacturing Work Cell to Promote Monitoring, Diagnostics, and Prognostics; 11
57. Carr V, Tah J. A fuzzy approach to construction project risk assessment and analysis: construction project risk management system. *Adv Eng Softw.* 2001; 32(10–11):847–57.
58. Petrovi DV, Tanasijevi M, Mili V, Lili N, Stojadinovi S, Svrkota I. Risk assessment model of mining equipment failure based on fuzzy logic. *Expert Syst Appl.* 2014; 41(18):8157–64.

Fig. 1.
ANSI/ISA-95 Functional Hierarchy [48].

Fig. 2.
Hierarchical Decomposition Methodology Flow.

Fig. 3.
Physical Decomposition Tree.

Fig. 4.
Physical Decomposition Tree with Sub-System Connections.

Fig. 5.
Functional Decomposition Tree.

Fig. 6.
Risk Reduction Options.

Fig. 7.
PHMC Robot Work Cell. a) Overall Work Cell. b) Close-up View of Robots Interacting with Work Fixtures.

Fig. 8.
Physical Decomposition of Multi-Robot Work Cell.

Fig. 9.
Functional Decomposition Tree of PHMC Use Case.

Table 1

Complete Physical Decomposition of the Multi-Robot Work Cell.

SYSTEM		S	MULTI-ROBOT WORK CELL											
Level	Var	Description												
SUB-SYSTEM	S1	Safety Systems												
	S2	PLC												
	S3	Drawing Robot	COMPONENT	Level	Var	Description					SUB-COMPONENT	Level	Var	Description
				S31	Robot Controller					S321		Joint 1		
				S32	Robot Arm					S322		Joint 2		
	S3	Drawing Robot	COMPONENT	S33	Drawing End Effector					S323	Joint 3			
				S41	Robot Controller					S324	Joint 4			
				S42	Robot Arm					S325	Joint 5			
	S4	Material Handling Robot	COMPONENT	S43	Gripper End Effector					S326	Joint 6			
								S421	Joint 1					
								S422	Joint 2					
	S5	Part												
	S6	Output Bin												
	S7	Work Fixture												
	S8	Input Tray												