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Hierarchical Modeling of a Manufacturing Work Cell to Promote Contextualized PHM Information Across Multiple Levels

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Abstract

With the ever-increasing demand for reconfigurability and modularity in manufacturing, industrial work cells are increasingly integrating newer and more diverse technologies to not only support the production of a wider range of parts, but also ease the repair or replacement of faulty systems and components. Complex relationships between different elements of a work cell originate from the integration of multiple layers of hardware and software needed to successfully execute the complicated manufacturing processes. Much work within the science of PHM (prognostics and health management) has been dedicated towards the management of some of this complexity via monitoring, diagnostic, and prognostic technologies. The strategic application of PHM technologies has been shown to effectively reduce equipment/process downtime and lower maintenance costs. Part of the challenge of PHM, particularly for manufacturers, is to know exactly where, and how to apply PHM within their work cell operations to gain the maximum actionable information. This problem is further compounded for small to medium-sized manufacturers (SMMs) who are typically limited in their resources and investment capital. Effectively designing and implementing PHM requires a fundamental understanding of the overall work cell and its constituent physical components and sub-components. Likewise, understanding the relationships between these physical elements and how these elements relate to one another is critical to determining how the degradation of one element will impact the degradation of another. The National Institute of Standards and Technology (NIST) is researching various PHM technologies that aim to enhance decision-making at the factory floor to promote smarter maintenance and control strategies. Part of NIST's research focuses on the decomposition of a work cell into a hierarchical structure to understand the physical and functional relationships among the overall system's critical elements. This physical and functional decomposition is a necessity to promote a meaningful rollup of diagnostic and prognostic information from the lower levels to the higher levels of the hierarchy. The hierarchy seeks to encapsulate how the overall system, and its subsequent components, will behave when an element within the system is compromised or begins to fail. Neighboring components and sub-components could be subject to the 'domino effect' or the 'ripple effect', making diagnosing the root cause of a cascade alarms difficult without some reflective model of the system. This paper presents NIST's efforts to

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develop a hierarchical decomposition methodology that will support PHM design and implementation within a complex work cell.

1. Introduction

To meet both production and quality needs, smart manufacturing facilities are constantly expanding capabilities and becoming more complex. This complexity is driven by an increasing presence and connectivity of programs, machine tools, sensors, and robotic systems [1-3]. The interplay of these often physically separate or functionally segregated elements can lead to cascading faults or problems caused by incipient events that may seem unrelated or go otherwise undetected. This research aims to develop a methodology as part of a smart manufacturing system prescribing a best practices approach towards identifying, capturing, and utilizing these relationships towards optimizing production line quality and maintenance scheduling. This builds upon and forwards the Industry 4.0 initiative [4].

The objective of this work is to describe development of an information consolidation and utilization model architecture based on a manufacturing process that has been systematically decomposed into its constituent functional elements. The critical relationships between elements can provide pertinent, concise, and contextualized information regarding the current and potentially future state of both the overall work cell and all constituent components and sub-components. This information can be used in operations and maintenance decision planning to maximize the productivity, efficiency, and quality of the manufacturing process.

2. Material and Methods

Understanding the health and state of a modern manufacturing facility is an increasingly complex task, particularly regarding the robotic work cell. Robotic production lines have a host of complex artifacts, control systems, and monitoring equipment that can be daunting to model [5-6].

Commonly, individual robots within a work cell are modeled separately [7], such models may include each sub-component down to the lowest traceable unit as a single model. Such models often can provide greater sensitivity to incipient problems than models operating at higher levels, such as those at the work cell level. An example of a low-level model could be a physics-based power consumption model, monitoring the electrical signals on a single robot, as opposed to a higher-level model that may monitor the total operational efficiency of the work cell. Both provide useful, yet different information. The low-level models are more sensitive to subtle changes in their respective unit, while a high-level model could be better at discriminating common cause problems. Rarely do higher level models directly incorporate information from the lower level performance models, despite the potential usefulness of this information.

Consider the example where three out of six robot motors are consuming more power than the command model predicts, but only Motor 01 has a bearing problem – the other motors are taking more load to compensate. To obtain the sensitivity to capture the earliest signs of

a problem, an individual model for each motor could be developed. To discriminate which motor is the true source of the problem, a higher-level model of the relationship between them is needed. We suggest that linking these two tiers of models could allow for best utilization of all the available information. Though this may seem a surmountable task in this example, the difficulty expands when scaling up to include all constituents of a work cell, or even a site wide facility.

3. Theory

One means of simplifying the task of modeling a complex system is to develop a hierarchical decomposition of significant interconnected sub-units that correspond to relatable structures within the system. Such a modeling architecture can aid in delivering and accessing the most important information at all levels. The decomposition of a manufacturing process can be physically-based, functional, or performance-based, and should capture both the physical and cyber-physical relationships within the processes. Monitoring these relationships allow for capturing the current system state as well as aid in diagnostics and root cause analysis. The level and complexity of the decomposition should reflect the needs of the end user both in terms of information requested and sensitivity desired. Other papers are targeted at describing this process in more detail are currently under review for publication.

Once a process or work cell has been properly decomposed into a hierarchy, this architecture can be directly translated into an information consolidation model. Each hierarchical subsystem is represented by node containing a self-contained sub-model that conveys the state or output of that subsystem by consolidating the outputs from all subsystems below it in the hierarchy. The lowest nodes contain the lowest traceable unit models, capturing the condition of individual elements (ex. a motor-operated joint) and are fed by some combination of sensor, operational, environmental, and control signals. These get linked to higher level subsystem nodes as prescribed by the hierarchy, which in turn, get linked to system nodes, and on up the chain to the top of the hierarchy. Using a topology prescribed by the decomposition of the system being modeled speeds design and development of the model. More importantly, this intrinsically provides useful decision trackability and information access points within the architecture.

Each node or sub-model is a self-contained 'local evaluator' that only processes data from the relevant tier's subsystems. Because of this, both construction and retraining can be done in a modular fashion. Although the primary function of each sub-model node is to consolidate and deliver information from the tier below to the tier above, their output could easily be queried by algorithms or users at any level of the hierarchy for aiding in more detailed investigations of anomalies. These 'smaller' sub-models are much easier to manage concerning inputs, parameterization, and performance testing. Additionally, should a system model be found to be flawed or new information becomes available after deployment, only that node's model need to be retrained instead of the full network, saving time, effort, and money in maintaining the full network of models.

4. Results

In broad terms, the type of model implemented at each node will be some combination of data-driven, and rules-based. Rules-based models (ex. physics equations) are useful where applicable, but are harder to implement, tend to over simplify, and generally would be applicable only on lower tiers. Two generally applicable modeling schemes that lend towards practical implementation of information consolidation at any level of the hierarchy include Bayesian Belief Networks (BBN) [8] and structured Neural Networks (NNs) [9]. BBNs have the advantage of intuitive construction and explicitly utilizing human experience or knowledge about a system. NNs have a less intuitive implementation but provide the ability to discover and adapt to relationships not explicitly programmed into the model but observing of the system over time.

Ultimately the choice of which implementation to use should be directed by the information available to the node sub-model both during construction and deployment, as well as the preferences and needs of the end user. Neural networks are best used if there is a large amount of verified historical data for the system (or sub-system) that spans the full range of expected operations and contains labeled examples of ‘good’ verses ‘bad’ behavior of the system. Conversely, if most of the knowledge about the system is based on human experience or ‘tribal knowledge’, then a rules-based model or BBN could be better suited as it can incorporate explicit probabilities or contingencies concerning the system. Obviously, exceptions to these guidelines and scenarios that lie somewhere between exist, but most cases fall into one of these categories.

Because the nodes are self-contained, if needed a combination of different model types could be implemented in the information consolidation model. For example, a physics model of motor performance could feed into a NN determining robot health, which ultimately feeds into a BBN that rates the reliability of the total work cell.

5. Discussion

The method of structurally linking self-contained models is largely analogous to the popular concept deep learning [10], commonly used with neural networks. An important difference of this work is that the sub-models themselves can be of a variety of types (NNs, etc.) and allow for various types of information to be propagated through the hierarchy. Potential information that could be used by the hierarchical model include reliability/diagnostic information, performance indicators, etc.

A hurdle in implementation of such an interconnected model network is the quality and availability of the data from lower tier sources. Disparate models may not have the same update rate or availability of reliable data. Node sub-models should be robust to missing or ‘bad’ incoming data. Future work will investigate method to validate the quality of incoming data before propagating it.

6. Conclusions

This work utilizes a methodological hierarchical decomposition of a manufacturing process into its constituent physical elements, functional tasks, and performance measures to identify critical relationships that influence process/equipment health degradation. This decomposition of relationships creates a topographic guide for construction of a network of evaluation models suitable for meaningfully aggregating degradation or diagnostic information for maximum knowledge use.

Biographies

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.

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Figure 1.
Example Hierarchical Decomposition

Figure 2.
Example Architecture