Selecting Optimal Data for Creating Informed Maintenance Decisions in a Manufacturing Environment

Don’t Drown in Trash: Curating ‘Minimum Viable’ Data Sets

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Abstract

Data availability within a manufacturing enterprise directly drives the ability of decision makers to effectively function and operate. The information needs of decision makers can vary greatly, based not only on the level at which the decision is being made, but also the perspective and desired effect of that decision. For example, an equipment-level operator needs direct knowledge of that equipment’s condition when deciding whether to operate that machine today; a production manager needs to know the number of operational machines when planning system-level operations; a maintenance manager needs knowledge of what maintenance tasks are in the queue and the availability of technicians. Although each decision is related, the information required to support each decision is distinct, and generated from sources that are often independent of one another. The granularity of information needed to make a decision is informed directly by what that decision is and any consequences of that decision. This paper discusses information and data requirements for maintenance decisions in manufacturing from multiple perspectives, including system, equipment, and component -level decisions. These decisions include both structured maintenance (planned and scheduled in advance of failures) and unstructured maintenance (performed immediately after a failure) decisions. The goal of this paper is to guide manufacturers who have limited resources to invest into a monitoring program to select a minimum viable set of data items to collect that support the decisions they want to make.

Introduction

The competitive edge in many industries, including manufacturing, is built upon fast, informed, and experienced decision making. Knowledge needed for informed decision-making differs based on the perspective and role of the decision maker. Decision support information requirements vary based on both the type of decisions being made and the level the decision affects, such as asset level, plant-wide level, or enterprise level. Reliability, maintenance, and operations planning all require specialized information resources to develop highly informed decisions in manufacturing facilities. What all of these levels and perspectives of decision making have in common is the need for information, i.e., data. However, not all facilities are equipped or have resources to devote to developing fully integrated or exhaustive data collection systems.

Sources of data are varied in modern manufacturing facilities. Each day a wealth of potential information is generated from equipment, sensors, and routine activities performed by plant personnel. Unfortunately, even in facilities with existing data collection systems, a majority of this information is not being properly captured and documented in a manner that allows for proper utilization of that data. While ideally data would always be managed with end uses and goals in mind, that is often not feasible as new uses and needs evolve with changing technologies and environments of factory floors. To maximize resource utilization and effectiveness it is important to continually assess the minimal set of decision making information needs and verify that the manufacturing facility's current information capturing policies and technologies can support them. When considering areas and systems with 'critical information', the goal is to develop a plan to collect a minimally viable amount of data that allows sufficient characterization and modeling of the system for intelligent decision making without devoting resources to unneeded or ineffective information. Too much data collection adds unnecessary processing costs and time as well as increasing the demands on properly storing and curating the information. Too little data collection could increase uncertainty or erroneous assumptions leading to suboptimal planning and lost productivity. These inefficient and ineffective scenarios can be avoided by structuring monitoring and analysis activities to collect and curate the smallest amount of data that sufficiently answers decision support questions for maintenance and operations management.

This paper is the first in a series making recommendations to help manufacturers develop viable monitoring programs and reference data sets to support informed maintenance decision making at various levels of the enterprise. Before focusing on technology solutions to capture and store data, it is also important to understand what constitutes useful amounts and types of data. This requirement list is largely informed by the intended use of the data being gathered. Both qualitative and quantitative sources of information are needed to produce comprehensive assessments of the condition, capability, and capacity of systems at all levels of the manufacturing enterprise. Finding the minimum viable information set requires identifying how much and what kinds of data are needed to enable efficient informed decision making necessary for competitive operations.

Background and Motivation

Gathering and assessing information as it moves in a manufacturing facility is a never-ending task that aids in all levels of facility functions. In many instances, manufacturers benefit from both quantitative data coming from embedded/OEM (original equipment manufacturer) and third party sensors, as well as qualitative data coming from human operators. Tools for collecting, storing, and processing these sources of information have evolved to allow the generated data to contain both more content and volume [Lee et al 2018]. Technologies for visualizing and interpreting data have also grown, promoting further utilization, understanding, and justification of any decisions made within or about a facility [Sackett et al 2006]. However, a number of concerns still exist in practical implementations of decisions using these data sources including: 1) potential for data capture to impede normal operating procedures, 2) lack of data interoperability, and 3) lack of validation guidance.

One concern when implementing information collection procedures and technologies is to ensure the information collection does not significantly interfere or impede normal operating procedures. This is true with both digital sensing, such as Industrial Internet of Things (IIoT) where computing and communication resources (bandwidth) for controlling the system may compete with data collection and transmission. Similarly, personnel performing value-add activities, such as completing maintenance tasks, often competes with time spent on filling out work orders and maintenance logs. While such procedures can provide large benefits for analysis and planning, they compete for time that could be spent performing other tasks.

An ideal reference data set would have balanced amounts of information representing all possible expected states of the equipment and facility. In most situations, creating this is impractical while maintaining normal operations. For example, many predictive diagnostic models at the asset or component level require one or more observed failures of a given type to characterize incipient fault symptoms. Generally, in real-world environments, every precaution would be made to prevent such failures making them impossible to observe and record. There is a need to develop different points/sources of data or model types to overcome this. Additionally, some system conditions could be exceedingly rare, or just not practical to enact at the time that the model is initially being created or tested. For these reasons, it is important to have mechanisms for adapting, updating, or replacing any information and decision support models as new data becomes available during the life of the system.

Unfortunately, even with modern data capturing technologies and procedures, it is rare for manufacturers to capture or have access to the 'perfect' data set for any given end goal. What limits the usefulness of a data set is not only the lack of balanced coverage of the information, but also a lack of annotation and context within data that is available. Ideally, when disparate sources of data relate to similar (or identical) kinds of system(s) or asset(s), those sources of data would be semantically linked or annotated in a manner that allows alignment and concurrent use for models and analysis. Rarely can a single source of information fully characterize a system or asset. Both quantitative and qualitative sources, such as maintenance reports [Sexton et al 2018] and sensors [Kong et al 2017] are needed for a full picture of the production facility. Manufacturers rely on standards for product information (e.g., STEP [ISO 10303], G-code [Kramer 2000], QIF [QIF 3.0, 2018]); equipment data (e.g., MTConnect [MTConnect Standard 2018]); and non-standardized data collected from Computerized Maintenance Management Systems (CMMS), as well as raw and processed sensor logs. Despite the availability of these data standards, the lack of interoperability of the associated data sources and integrated third party tools highlights practical concerns of linking dissimilar file formats. This also points to a need for intermediate platforms for information extraction and collection that can be accomplished in a practical way useful for various levels of informed decision making. More basic than information extraction, there is a need for a standardized manner to discover and/or assign connections between the files that can facilitate information discovery.

There are few standardized methods for determining how much and what kinds of data are necessary to build models or perform validation on decision support platforms at a given level of the enterprise. Even when restricting to a single decision level, such as the equipment or component level, available models each have their own requirements regarding active and historic data [Si 2011]. Adding to this, even if a ‘perfect’ data set were to exist that could translate information across all levels of the enterprise, no consistent guidance is given on how to turn this data into actionable intelligence for decision making.

When developing an information and decision support structure, there are two philosophies for approaching this: ‘what is the minimum data I need to answer my questions?’ versus ‘what questions can I answer with the data I have available?’. The authors approach the issue from the first perspective, which implicitly requires decision makers to understand and focus on fewer, but higher impact questions. This builds from the idea that it is not realistic, useful, nor feasible to capture all information. Our research goal is a framework guiding the development of minimum viable data collection and storage that satisfies all critical decision support needs without over burdening employees or other resources with unnecessary tasks of curating and dissecting information of limited value. The next section examines some practical steps that can be used in developing both historical and ongoing data sets for characterization and modeling of system states for informed decision support.

Methodology

This paper explores methods for developing ‘minimally viable’ data sets required for informed, intelligent decision making. The first step in determining the minimally viable amount of data collection focuses on decomposing the functions and assets of the factory into linked levels and subdivisions that represent the physical and functional structure of the facility [Li et al 2018]. This architecture can be used to help model and identify the most critical links that either contain or transmit data and information needed to make useful observations about the state of the facility [Sharp 2018]. The ISA-88 and ISA-95 family of standards prescribe an enterprise hierarchy: field device (sensors and actuators), control device (control devices, controllers, embedded controllers), and station (machines, robots, intelligent logistics/material handling). For the purposes of this paper, the authors focus on a simplified hierarchy: system, equipment, and component levels. Some additional context and characterization of the component, equipment, and system is provided below.

Within the context of maintenance decisions, the “bottom” of the decomposition hierarchy is defined by the lowest repairable unit (LRU) and any associated performance or condition indicators that are monitored. The specific list and level of LRU assets will be unique to each enterprise, but the definition generally centers on the lowest level component that can be maintained, fixed, or replaced on site, and whose failure would have a negative impact on the site’s performance or efficiency. Some examples of LRU could be bearings, sealed motors, hydraulic actuators, or other assets that are generally repaired or replaced on site. Given this list, it is important to note that although most LRUs are found at the component level, in certain situations this could be found at either the equipment or even system level. For example, if a specialized milling machine must be maintained by an outside contractor, it may only be necessary for the factory to monitor if the milling machine is maintaining high level performance indicators. A system level LRU could be a digital software system, such as a third party off the shelf CMMS that might simply be replaced with another if it fails to meet the facility’s needs or proves faulty / obsolete.

Components are physical entities defined by a single, static functional capability controlled parametrically by well-defined inputs and expected effects. Each can be maintained (or replaced) independently of the equipment it's a part of. Components can be composed of other components (i.e., sub-components). Most LRU assets are found at the component level. Examples of components could be pumps, bearings, actuators, wiring, etc.

Equipment are composed of components and/or other equipment, and are described as "functionally complete" units. Information and data from them supports decision-making focused on real-time process execution. Concerns regarding the equipment level are embodied in supervisory control systems (SCADA), advanced-process control and optimization (APC-O) and programmable logic controllers (PLC). From the maintenance perspective, the availability and capability of the equipment is directly impacted by its components. While an equipment asset may be "maintained" or inspected, maintenance activities most often address the lower level components that comprise the equipment. Examples of equipment level assets could be milling machines, robotic manipulators, casting machines, or other assets that perform one or more tasks facilitating production and have components within them that can be replaced or repaired on site.

Systems are composed of equipment and subsystems and focus on completing one or more production tasks. Information relating to systems is used for decision-making focused on material/job flow, resource utilization and contention, and enterprise concerns such as throughput, cycle-time, quality, and cost. These concerns are often embodied in manufacturing operations management (MOM) and manufacturing execution systems (MES). Additionally from the maintenance perspective, systems are not individual units that can be directly maintained, but rather has its capability, capacity, and performance defined by its constituent units (subsystems and equipment assets). Work cells, work stations, production lines, or even full facilities could be considered systems and collections of subsystems from an enterprise level.

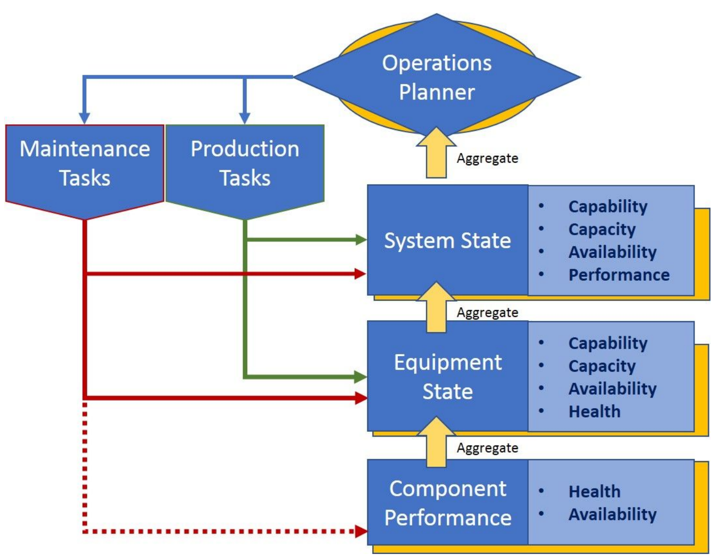

Figure 1: Information Level Flow Diagram

Each level of this relatively simple hierarchy (component, equipment, system) provides state, capability, or performance information that is aggregated upwards to inform the next level (Figure 1). In this simplified scheme, information from component and LRU level assets is propagated upwards to inform about the operations state and condition of the associated equipment. Equipment state and condition, in turn, is used to inform its system's operations and performance. The system state, aggregating many pieces of information, is input into an operations planner that prioritizes and schedules both production and maintenance tasks that are fed back through the various levels. Should additional information be required at a higher level than it is typically transmitted to, it would ideally be a simple matter to drill down and query any information set without losing any information. Figure 1 is a simplified flow chart that represents an implementation of this process. Alternatives or variants of this diagram could also exist, but the basic structure of condensing and feeding information upwards to a planner that then directs operations is the idea explored in this paper.

Figure 1 indicates that it is the primary job of the component level to populate maintenance tasks based on both condition- and calendar-based events for any given LRU. The equipment level information may also provide maintenance tasks that cross-cut multiple components, or may not have been easily discoverable based upon component level monitoring. Evaluating the criticality of each maintenance task is mostly performed with contextual information from the equipment level. Equipment level information also supports coordinating maintenance tasks that should be performed together. Coordinating maintenance tasks is possible when a planned operation provides an opportunity to performance additional maintenance while minimally impact operations, e.g., replacing a faulty valve when a machine is on a planned service outage for routine lubrication change. This coordination function can similarly be performed at the system level when managing linked equipment. Full maintenance scheduling is best accomplished at the system level where all available information about scheduled operations can be synthesized and optimized into a plan that incorporates all relevant resource and criticality information.

The definitions of the various information tiers are intentionally flexible, leaving room for interpretation on how a system is decomposed into its constituent subsystems, equipment, and component assets. Ultimately, the use and interpretation of these definitions can be application-specific to best suit user needs. For example, equipment may be composed into other equipment such as a machining center being decomposed into a constituent material handling robotic arm and a machine tool. Additionally, one could define digital equivalents of each of these levels that can be monitored and maintained in an analogous fashion to the physical assets presented in this paper. For simplicity, digital assets of this nature such as communications exchanges, cyber security protocols, operating systems, etc. are largely ignored with regards maintenance in this paper. The decisions and data requirements for each level are described in the sections below.

System level:

At the system level, we are primarily concerned with how maintenance decisions impact performance metrics such as throughput, cycle-time, and cost. From the maintenance perspective, important information is current and future equipment state and characterizing dynamic behaviors, such as availability, capability, and capacity. Equipment standards, such as MTConnect, report whether a machine is available or unavailable (up/down) and possibly busy/idle. The second aspect related to planning and scheduling focuses on creating and incorporating predictions of future unavailability -- whether due to scheduled/planned maintenance tasks or estimated unplanned maintenance. There are several ways to incorporate information about expected availability into scheduling methods, dependent upon the specific available information [Vieira et al, 2003].

Accurate descriptions of equipment capability, capacity, and state are essential for operations management decision-making; primarily the scheduling of production and maintenance operations. This data collection enables identifying and characterizing bottleneck equipment (workstations and systems). Maintenance operations management decisions can then incorporate this information to determine maintenance priorities.

A brief summary of general system-level decision information and corresponding data requirements is presented below:

Classes of decisions:

Which production jobs can be assigned to a piece of equipment? Is it available and capable?
When should maintenance tasks be generated (planning) and performed (scheduling)?
How to prioritize maintenance jobs? When should jobs be performed and to what extent?
Which replacement components (or equipment) should be stocked in inventory?

Supporting Data:

- Equipment State (*Current and Future*)
  - Capability
  - Availability
  - Capacity
- Maintenance Queue
  - Priority/Criticality of tasks
  - Availability of resources (personnel, material, parts, etc.)
  - Impacts on throughput
  - Coordination of tasks (i.e. opportunity-driven priority)
- Production Queue
  - Priority/Criticality of tasks
  - Availability of resources (personnel, systems, material, parts, etc.)
  - Current buffer states

Equipment level:

At the equipment level, decisions are less about if the equipment *should* be run, and more about if it *could* be run. This centers around the determination of both the equipment health and availability, as well as capability and capacity; the determination if there is a configuration of the equipment that will allow for safely fulfilling all requirements of the requested duty cycle. Synthesizing health information from the constituent components' health and making determinations of overall health as well as capacity will largely be diagnostic in nature. This information is also used to assess criticality of and assign priority to component maintenance requests.

Root cause investigations and determinations of potential solutions to the problem provide critical information for decision makers in the event of a failure. Additional information, such as the amount of required time/effort for a given solution, is also useful. Determinations of impacts on production and throughput would generally be made in context of the system level.

Another equipment level decision is the coordination between maintenance tasks. This is different than the assignment of criticality of the task, and focuses on the benefits from performing simultaneous maintenance activities --- effectively judging if the extra time spent at this piece of equipment will affect other maintenance jobs in the queue. These 'opportunity-driven' tasks can be aligned to minimize the total downtime of a given equipment.

Based on these decision requirements, much of the data and information collected around this level should support investigations relating to failure diagnostics, prediction, and prevention. The decision makers need to predict when the equipment will go down next, what will cause the failure, how long the corresponding maintenance will take, and how much additional time is required for the equipment and any associated process to resume normal operations. While a large portion of this information is fed from the component level, the prioritization and alignment of maintenance tasks can only be determined with the contextualization of the equipment level. Common examples of equipment level information come from raw and processed sensor signals from the component level (e.g., vibration data) as well as qualitative data in Maintenance Work Orders (MWOs) (e.g., description of the problem). The different decisions and supporting data is summarized below:

<u>Classes of decisions:</u>

- Should I operate this equipment?
  - Are all critical components in a state to allow safe completion of the planned duty cycle?
  - Can the equipment produce parts or perform services to the required minimum level of quality in its current state?
  - Can the equipment be in a different configuration to better meet requirements?
- What maintenance activities should be prioritized?
  - How critical are component level maintenance requests?
  - What, if any, is the equipment level relationship between diagnosed component degradation?
  - What is the criticality and time horizon of potential faults or failures?
  - Should any maintenance activities be grouped for simultaneous execution?
  - What are the maintenance solutions to prevent (or delay) failure and are these solutions cost effective to implement? If so, how long will it take to implement the solutions?
  - What is the root cause for an observed failure?
  - Has an observed failure happened before?

- What can be done to fix observed faults, failures, inefficiencies, or other problems and how long will it take to fix?
- How can I prevent similar problems in the future?

Supporting Data:

- Maintenance Work Order Data
  - Descriptions of previous faults/failures/etc. and corresponding solutions
  - Time spent on faults/failures and solutions
  - Technician(s) sent to solve fault/failure/etc.
  - Resources (e.g., parts, tools) used in addressing the fault/failure/etc.
- Equipment Data
  - Equipment manuals and schematics
  - Taxonomy of components in equipment
  - Population fault/failure rates
- Component States
  - Health information
  - Predicted faults/failures/etc.
  - Component level maintenance requests

Component level:

Component information monitoring focuses on two areas. The first area determines the current capabilities of the equipment: if and at what capacity or workload a component can be operated. The second relates to populating maintenance tasks via degradation monitoring, diagnostic fault cause analysis, and prediction of probable future states of the component. Some of this information needs to be contextualized at the equipment level, where understanding the relationships between components is essential, e.g., will this component hurt production efficiency, lower product quality, etc.? Even so, the bulk of the data/information regarding maintenance needs and even some decisions are collected/made at the component level.

The most simple information that can be captured is if the component currently able to operate, or if it is currently exhibiting a 'failure' condition. This can be a soft failure where the component is unable to perform at a minimal operating level or has deviated beyond allowable limits from expected behavior; or a hard failure, typically catastrophic, where the component is unable to function at any capacity. This class of information could loosely be categorized as a minimum state observation for the component. While this observation can provide decisions on 'go/no-go' scenarios, the amount of insight given is very minimal.

The next progression of component level decision information involves accessing the overall health and capacity of the component. This demand for extra information creates a corresponding amount of additional demand on the data required. There are an abundance of sensor types, algorithms, and models that can be used to access the current condition of a component.These assessments can be qualitative, quantitative, definitive, or probabilistic, and are determined by either direct or indirect measurements about the system [Si 2011]. While different models and algorithms may impose different data needs for their construction, the general class of tools that measure or estimate the specific condition of a component all rely on some level of sensing capabilities. In some cases, certain condition monitoring tools can even benefit from higher level operational data, such as workload plans, maintenance activities, etc. A more in-depth breakdown of the data requirements for various modeling approaches (physics, rules-based, data driven, etc.) is beyond the scope of this brief paper, but will be addressed in future works. One metric useful at this information tier is the Current Life Consumed (CLC), which often corresponds to the current amount of degradation detected in the component, normally as a percentage of some failure threshold. This information tier encompases active monitoring of a component.

The component conditions assessment can also extend to predicting future states. This is accomplished by first knowing what are the current/future needs and expectations from the system, and second - given these expected stresses and demands - predicting the probable future condition and capacity of the component. These information types and analysis broadly fall under the category of prognostics. The ‘prognosing’ of future states can be longer term (e.g., for scheduling, maintenance, and planning), or shorter term that focuses exclusively on the current or immediately upcoming duty cycle. Some form of either definite or probabilistic operational plan must be defined or inferred for this analysis, which yields information beyond that available at the component level. This shows the relationships between multiple information levels and areas of a factory setting. Again, the specific tool or algorithm used for the prognostic assessment of the equipment will have specific needs of the component level information, either historical or current. A common metric for these types of analysis is a component's Remaining Useful Life (RUL). A brief summary of general component level decisions and corresponding data requirements is presented below:

<u>Classes of Decision:</u>

- Can a component, within a piece of equipment, be marked available for a requested operation?
    - Is the component currently occupied with some other task?
    - Is the component functioning or has it failed?
    - What are the state and time horizons of any currently identified incipient faults?
    - Can this component meet the current/future needs?
- What are the current or future maintenance actions required for this component?
    - Are any calendar-based or cycle-based preventive maintenance actions upcoming?
    - Are there any condition-based maintenance actions upcoming?
    - Are any corrective repairs needed?

<u>Supporting Data</u>

- Capacity Specifications
    - Possible configurations of component
    - Nominal work loads
- Condition assessment information
    - Human interrogators
    - Predictive models

    - Sensors
- Anticipated Future Performance
    - Planned duty cycles
    - Probabilistic modeling
- Maintenance planning
    - Needed resources
    - Maintenance work order data
    - OEM Maintenance recommendations

Summary and Conclusions

This paper discusses maintenance decision making and data needs at three levels: component level, equipment level, and system level. There is strong interplay between these levels with information flowing upwards from the component level LRUs, into a more contextualized equipment level of information and finally into system levels of information with pertinent decision support at every tier. The primary blocks of creating a maintenance action plan have different information needs at each of the three levels. A summary of example decisions and supporting questions for the various information levels is shown in Figure 2. These are not the only decisions or possible groupings of information that could be applied to a factory setting.

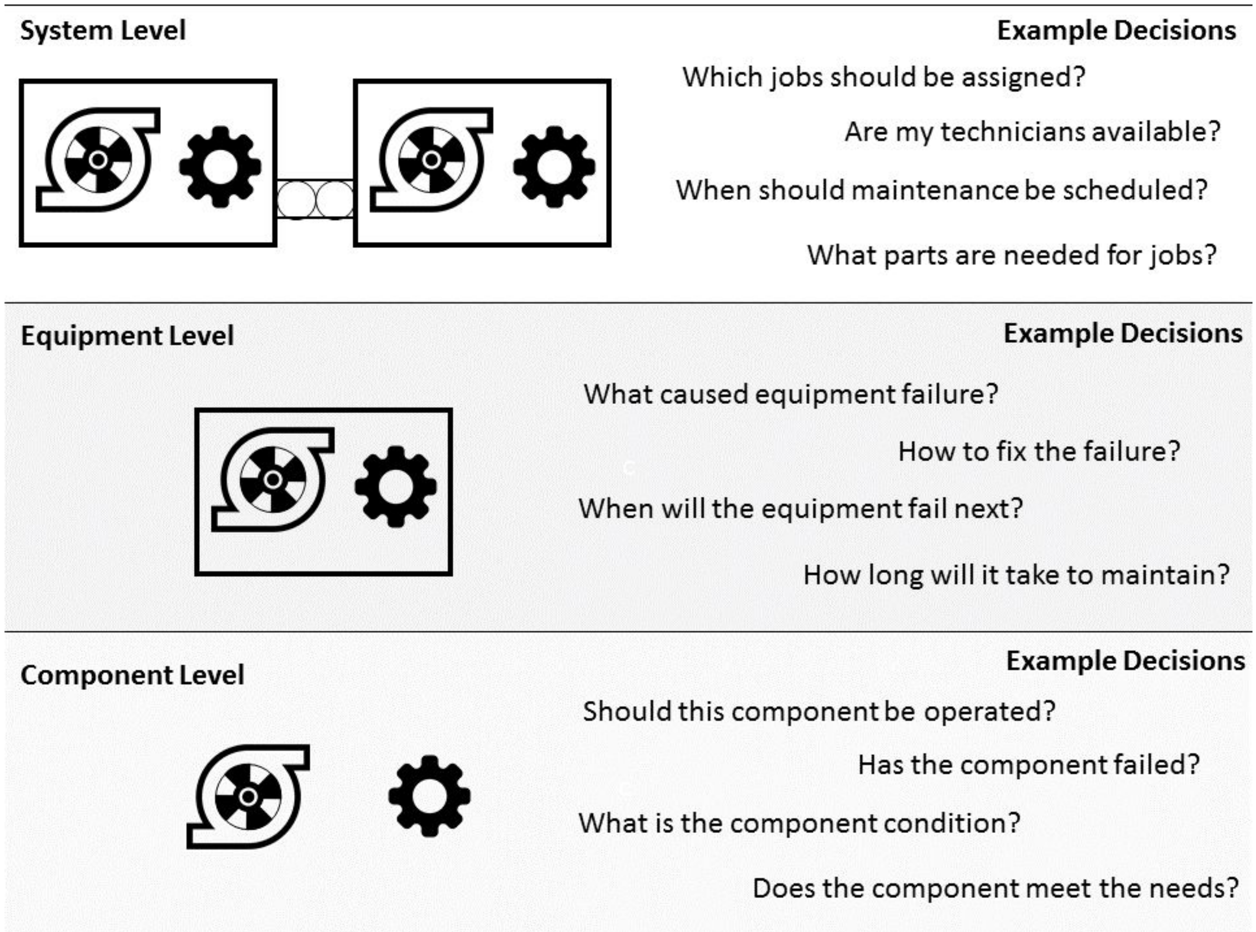

Figure 2: Maintenance Decisions and Corresponding Levels

The primary goal of this work is to present some common questions and decision support needs by way of information gathering. This is intended as the beginning steps to creating a working guide for industry practitioners to develop their own optimized information gathering and decision support network. Resources dedicated to gathering specific sources of information should be tailored to the explicit decision support needs of the managers, operators, and technicians. If an asset is not deemed mission critical, or is otherwise placed into a 'repair on failure' category, there is no need to invest in expensive data collection and storage tools. Conversely, if an asset is *highly* critical, there is a strong case for extensive monitoring and modeling tools to ensure that the asset rarely, if ever, experiences a failure. Other assets that could merit more monitoring tools are those that are creating large amounts of maintenance work orders, either calendar or condition-based. The extra monitoring and analysis could help to optimize the amount of maintenance and/or discover different operations or maintenance practices that could optimize the types of maintenance performed and thus reduce downtime.

The next steps in this work will look at a specific decision at the system level and create a framework for determining the correct data from both the equipment and component levels. This implementation will lead to a more appropriate roadmap of standards and research needed in this space.

NIST Disclaimer

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