Published in final edited form as:
*J Comput Inf Sci Eng*. 2017 September ; 17(3): . doi:10.1115/1.4037178.

# Towards Knowledge Management for Smart Manufacturing

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## Abstract

The need for capturing knowledge in the digital form in design, process planning, production, and inspection has increasingly become an issue in manufacturing industries as the variety and complexity of product lifecycle applications increase. Both knowledge and data need to be well managed for quality assurance, lifecycle-impact assessment, and design improvement. Some technical barriers exist today that inhibit industry from fully utilizing design, planning, processing, and inspection knowledge. The primary barrier is a lack of a well-accepted mechanism that enables users to integrate data and knowledge. This paper prescribes knowledge management to address a lack of mechanisms for integrating, sharing, and updating domain-specific knowledge in smart manufacturing. Aspects of the knowledge constructs include conceptual design, detailed design, process planning, material property, production, and inspection. The main contribution of this paper is to provide a methodology on what knowledge manufacturing organizations access, update, and archive in the context of smart manufacturing. The case study in this paper provides some example knowledge objects to enable smart manufacturing.

## 1. INTRODUCTION

The global manufacturing industry is currently undergoing a transformation towards smart manufacturing [1, 2]. Smart manufacturing is the synthesis of advanced manufacturing

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capabilities and digital technologies to collaborate and create highly customizable products with optimized cost, lead time, quality, societal well-being, and environmental stewardship [3]. The concept of smart manufacturing is closely related to knowledge-driven decision making to meet customer demands for products, technology challenges in security and disruption, and changing workforce skills. Advanced information and manufacturing technologies are key enablers to smart manufacturing as digitized knowledge enables manufacturers to make timely and secure decisions. Internal knowledge constructs (described in Section 3.2) about specific markets, products, material information, and processes drives these decisions. To make decisions in various stages in a product's lifecycle, knowledge about each manufacturing process must be readily available to decision makers. Currently, knowledge is not completely captured in a digital, searchable form in all phases of the lifecycle. For example, design drawings, process capability graphs, equipment pictures, manufacturing operation tables, production schedules, statistical-process data interpretations, and engineering change requests are often not fully integrated. Furthermore, engineering knowledge is embedded in various stages in the product lifecycle in forms of rules, logical expressions, ontologies, predictive models, statistics, and information extracted from sensors in real-world situations, such as production, inspection, product use, supplier networks, and maintenance. It is now a goal for organizations to achieve streamlined knowledge capture and curation through knowledge management. Mechanisms within organizations to digitally capture and store these knowledge entities are often not mature enough to be fully realized.

It is noted that the recent development of technologies and tools provide optimism. For instance, MTConnect [4], web-based engineering tools, and real-time monitoring applications provide steps forward in realizing a truly integrated digitized lifecycle in practice. To facilitate this progress, a set of knowledge management constructs are proposed to support knowledge integration and exchange for smart manufacturing. Though it has been argued that benefits of knowledge-based engineering have already been realized within organizations, distributed deployment across an entire supply chain or multiple organizations has not yet been achieved [5]. This further motivates the development of knowledge management technologies for unifying knowledge in design, manufacturing, inspection, and supply chain management for smart manufacturing.

The scope of this knowledge management development work is focused on the digital thread [6] to enable timely access to knowledge throughout a product lifecycle, including design, production, and quality control. In this paper, a knowledge management approach is described to enable open access to design, manufacturing, and inspection data in a product lifecycle. Figure 1 explains the relationships between data, information, scientific understanding, knowledge, and autonomy in smart manufacturing. Level 1 is the basic (or raw) data level [7]. Here, data is collected from sensors, the machine itself, or generated by software through simulation. Level 2 is about information [8]. Information in manufacturing includes descriptions about the workpiece, parts, tools, and materials. Information is usually static and answers questions on “what, when, who, and where.” Information is a result from the interpretation of data. Level 3 is the understanding level which focuses on answering the question of “why.” This stage encompasses a deep understanding of manufacturing processes, material properties, and machine performance. Physics-based predictive-model development is the activity on this level. Level 4 is the knowledge level, including processes, equipment, supplier selection, and logics or rules based on the production design and equipment capabilities. Knowledge answers the question of "how," usually based on the why described in Level 3. Note that Level 3 and Level 4 can be interchangeable when the understanding of "why" is based on knowing how materials are transformed into products. Level 5 is the autonomy level. It involves further processing and applying the knowledge of manufacturing science for learning, cognition, and adaptation. In this paper, we specifically focus on Levels 3 (understanding) and 4 (knowledge).

Figure 1 presents the proposed levels of knowledge engineering integration. Once data-capture mechanisms and the fundamental software and hardware are implemented, the next activity is to generate and curate manufacturing knowledge for users to query. After multiple uses of the associated databases, patterns and common practices can be identified and ultimately lead to generalized prediction models that can steer decisions across the lifecycle.

To bring perspective to knowledge management, Figure 2 illustrates an example of knowledge creation in the context of quality assurance. Given a scenario for manufactured part measurement, measured data is converted to information by adding tolerance specifications. Based on the information, science-based predictive models for describing geometric variations, e.g., shrinkages, may be developed. With an understanding of geometric variation in manufactured parts, knowledge is then generated for process, material, equipment, and operator's variations. The knowledge can be used for the decision-making process of accepting or rejecting the inspected part. These perspectives will be abstracted to a more generalized set of concepts to be adapted to various new situations in the context of smart manufacturing.

Based on the previous work at the National Institute of Standards and Technology (NIST) on standard data models for manufacturing systems integration [9], this paper describes a new knowledge management approach through identification of key components of knowledge in smart manufacturing, including design (conceptual, embodiment, and detailed), planning (design process planning, resource planning, process planning, and quality control planning), production (scheduling, task monitoring, and process control), and quality control (measurement and analysis). The proposed methodology enables knowledge sharing for decision making in addition to product-process data integration across these four key components.

The rest of the paper consists of the following sections. Section 2 reviews available literature in smart manufacturing and knowledge management. Section 3 describes the knowledge constructs to be used in cognition, learning, and adaptation in smart manufacturing. A case study shows how new knowledge management functions in the real manufacturing of products. Section 4 discusses some implications of the described methodology and Section 5 concludes the paper and suggests future directions.

## 2. STATE OF THE ART REVIEW

This section provides a review of related research generally applicable to knowledge modeling, frameworks, representations, sharing, and analyses for smart manufacturing. Here, the domain-specific knowledge includes design, planning, production, quality control, and the supply chain. Applications of manufacturing knowledge include ontology development, lifecycle assessment, quality-problem traceability, and product-design improvement. The lack of a mechanism for the engineering and management of knowledge for smart manufacturing is identified at the end of this section. The reviewed results serve as the basis for developing a methodology for knowledge engineering and management.

### 2.1 General Framework Development

A framework provides "guidance and rules for structuring, classifying, and organizing architectures" [10] and necessary information on an abstraction of a system's components, its functions, scope, and guidelines to develop systems or standards. In this paper, we present a first step for developing such a framework by presenting a methodology for capturing knowledge generated in a smart manufacturing system.

Smart manufacturing can be implemented and operational if data and knowledge are integrated with applications [1, 2]. Papazoglou et al. [11] demonstrate the potential of operationalizing data and knowledge through a sensor-driven reference architecture in an automotive manufacturing network. Their work presented several use cases for re-purposing common knowledge models across a multi-stakeholder value chain. Using a similar approach, Srinivasan [12] develops a standards-based integration framework for capturing product data and meta-data for product lifecycle management (PLM). The framework was demonstrated through a reference implementation of a service-oriented architecture (SOA) for PLM by a leading automotive supplier. Others have developed similar data-integration frameworks and related methodologies specifically for manufacturing planning and production. Lechavalier et al. [13] propose a framework to integrate data analyses for custom data viewing and analytics. Similarly, Lee et al. [14] propose a cyber-physical systems (CPS) architecture with the goal of clearly defining CPS and setting the stage for more re-usable analytical methodologies related to smart manufacturing. In this paper, we present a methodology that aims to enable smart manufacturing knowledge capture and curation, remain complementary to the above-mentioned frameworks, and empower advanced analytics.

### 2.2 Data and Knowledge Modeling

An ontology is a formal information representation of a body of knowledge on an entity, such as a physical object, person, or system. Gollapalli, et al. [15] develop a technique to discover heterogeneous ontologies and apply queries for semantic reasoning. Ameri et al. [16] develop a knowledge-organization system for developing new ontologies related to manufacturing while ensuring semantic interoperability with existing thesaurus representations. Similarly, Arnold and Rahm [17] introduce an approach for mapping semantic relations within an ontology and between ontologies. These research efforts highlight the importance of improving the interoperability of data models. Often, metamodelling techniques are required for merging diverse sets of data models, incorporating more formal descriptions of the precise mapping of concepts across multiple models [18].

Different types of data models and ontologies are commonly used to formally represent data and to extract information and knowledge from data [19]. Data modeling is a means of organizing data for information extraction and has been implemented extensively within product engineering. For example, Wasmer et al. [20] present the use of a data model to describe and optimize a constrained mechanical design by a teaching-learning algorithm. Ameri and Dutta [21] develop a product-data model for handling and sharing engineering changes on product designs across different organizations in a manufacturing enterprise. Physics-based modeling is a type of modeling where knowledge of known physical phenomena is embedded in the model of a process, such as additive manufacturing or machining process planning and in-process control [22]. Modeling is useful in data analytics, wherein reusable knowledge guides decision making in resource optimization, better process control, and design changes for smart manufacturing [23].

### 2.3 Product Lifecycle-related Models

Product lifecycle data in this paper refers to data that represents design, processes, materials, reuse, remanufacturing, and disposal. Product lifecycle data can also include the data from supplier networks. Rebitzer et al. present a product lifecycle assessment methodology that includes functional components, tools, analytical methods, and applications [24].

In the design domain, a review of knowledge representation in product design reveals knowledge-management problems in (1) sharing and creation of a cross-organizational network of design knowledge, (2) bottlenecks in knowledge acquisition for industrial applications, and (3) lack of design knowledge information models for users [25]. These challenges have recently motivated new research in this area. A tolerance standard has been developed and can be used to represent and store product data and design intent [26]. A product assembly model can be used to store and represent knowledge of a product-component structure and the assembly sequence [27]. A view on traceability of heterogeneous knowledge representations has pointed out the importance of knowledge management for better product design [28]. These considerations encompass a portion of the lifecycle and can be expanded to manage the knowledge and drive knowledge sharing in a product's whole lifecycle.

Furthermore, lifecycle knowledge has been specifically applied to the design phase to support decision making processes. It has been argued that most designs are combinations of existing designs [29]. As a result, a number of efforts focus on reusing product lifecycle knowledge to inform concept and detailed design models. According to a study by Khadilkar and Stauffer [30], about 50% of user-queried, historical design information was shown to be useful during the conceptual design phase and 70% of queries were useful during redesign activities. A related effort demonstrated a design-knowledge-reuse methodology to produce new concepts for high vacuum pumps for the semiconductor industry [31]. A new set of product representation was developed that is aimed to promote knowledge reuse in design [32]. With respect to material selection in design, PreMAP, a material-driven knowledge database, allows for simulation of sets of unobserved design variables based on existing analyses [33]. This has significant implications to the detailed design stage for optimizing design features based on existing product knowledge.

### 2.4 Technical Barriers and Needs

Although there has been significant work related to representing knowledge for a variety of manufacturing workflows, there is a gap in representing knowledge from the entire lifecycle. We identified the gap by comparing the goal described in Section 1 with the literature review above. The gap has left opportunities for advanced analytics and design optimization still unrealized.

Based on the review, specific barriers and needs are identified:

1. Knowledge representations are dispersed, and a universal access method is needed to enable different manufacturing and supplier organizations to share knowledge about product design, manufacturing resources, and material specifications.
2. A method for knowledge acquisition with fully digital representation, web-based access, and automatic updates is not available.
3. Knowledge management is a complex issue. A methodology is needed to provide guidance for developing knowledge bases to meet manufacturers' needs in making timely and effective decisions.

## 3. KNOWLEDGE MANAGEMENT METHODOLOGY

This section describes the following key components in knowledge management methodology for smart manufacturing: (1) the context for which knowledge management enables smart manufacturing, (2) knowledge constructs for representing knowledge, (3) an elaboration of applying knowledge within manufacturing units and operations [34], and (4) an organization of different knowledge accessible by applications illustrated through a case study.

### 3.1 Context of a Methodology

Knowledge management is the activity of generating, processing, and storing knowledge within knowledge bases. Supporting activities include creating, accessing, retrieving, updating, and removing knowledge (and its accompanying structured data) from a knowledge base (which is further described in Section 3.2). Figure 3 illustrates the major components in the context of knowledge engineering. Data, a priori knowledge, as well as conditions are inputs to the activity of knowledge engineering. Examples of conditions are the working environment conditions, the state of a process, the state of equipment, the state of workpiece material, and the state of operators. Knowledge is captured in knowledge constructs as described in Section 3.2.

From this perspective, data is generated from engineering activities, including quality management, maintenance practices, and supplier considerations (e.g., capabilities, readiness, and expertise). Engineering activities can also include requirement selection, design, manufacturing planning, scheduling, process control, diagnosis, and prognosis. During these activities, a priori knowledge is generated in the form of statistical distributions, measured data from similar processes. Conditions include data related to the state of manufacturing, such as processes, machines, and shop floor material flows. Knowledge engineering[2] is usually driven by a specific goal of the company. A goal is derived from the company's mission, executives' vision, and management strategy. The generated outputs from knowledge engineering include a posteriori knowledge for decision making. A posteriori knowledge can be used for adaptation of engineering activities, such as redesign of products, changes in manufacturing process planning, rescheduling, and modifying the quality plan. Extracted knowledge is an important asset of the company.

The distinction between a priori and a posteriori knowledge is important for understanding knowledge management for smart manufacturing. In their formal definition, a priori knowledge describes (for instance) a manufacturing process independent of experience, while a posteriori knowledge refers to the manufacturing process dependent on experience [35]. We choose a slightly different interpretation. For a manufacturing process, a priori knowledge could include historical process data of similar legacy products. Such knowledge is necessary for developing a collection of rules, models, and statistics that predict the behavior of that manufacturing process. In contrast, a posteriori knowledge would include the observations and operator experience specific to that manufacturing process.

The above described knowledge engineering context forms a basis from which components of knowledge management for smart manufacturing are developed. One major component allows for handling knowledge of various forms in a generalized architecture. The other major component is for processing and applying the stored knowledge.

### 3.2 Knowledge Constructs

Smart manufacturing knowledge bases store knowledge relevant to smart manufacturing. To properly curate and retrieve knowledge objects from a database, it is necessary to develop constructs that capture a wide range of information types while, at the same time, are complementary to each other. These constructs are designed to support handling and applying knowledge in all possible formats, applications, and available languages.

The types of knowledge constructs stored in a smart manufacturing knowledge base should include the following:

- **Rules**: if-then rules are commonly used in, for example, process planning, scheduling, detailed design, supplier selection and material or equipment selection.
- **Logics**: first-order predicate logic, description logic, and intuitionistic logic [36] are commonly used in, for instance, process logic description, product feature relationships, process capability, and equipment capability.

[2]Knowledge engineering includes a systematic approach to extract, represent, store, and retrieve knowledge to enable smart manufacturing.

- **Ontology**: developed in logics or modeled using software engineering tools to describe, for example, a body of knowledge on a product design, process plan, production schedule, or shop floor layout.
- **Physics-based predictive model**: developed using physics principles to describe the behaviors of a process, such as for a material removal process, material forming process, or material deposition process.
- **Bayesian statistical model**: developed based on the Bayesian statistical principles to reason or predict events in a manufacturing process or system.
- **Facts**: known facts and facts newly discovered from the data are useful knowledge for smart manufacturing.

There are available languages for adopting the proposed knowledge constructs. For instance, the Predictive Model Markup Language (PMML) [37] is a language for describing data and knowledge for data mining, and the Knowledge Discovery Metamodel Markup Language (KDMML) provides a format for knowledge found in different information models to facilitate exchange [38]. Knowledge bases are, thus, created to store knowledge in different formats, allow access, and enable the ability to update for users of manufacturing systems. The relations amongst users, applications, and knowledge are discussed in the following section.

From a global perspective, Figure 4 illustrates the associated attributes of the knowledge construct and its interface to an eventual knowledge base. As shown in the figure, it is possible that the knowledge construct lacks input types, e.g., a priori knowledge, conditions, and data. However, it is a requirement to store the goal and a posteriori knowledge into the entity. A posteriori knowledge includes, but is not limited to, stakeholder decisions, specific actions, and engineering analyses. The goal is the driving force for solving a problem or achieving an objective, such as becoming smarter in manufacturing. A posteriori knowledge typically comes from the analysis of a priori knowledge to take appropriate actions to achieving the goal.

### 3.3 Application to Smart Manufacturing

The knowledge base architecture described above is designed to support decision making in different levels and timespans in a manufacturing facility. This architecture can be categorized into the following units: company, factory, production line, workstation, machine, and kit/labor to enable the synthesis of advanced manufacturing capabilities to increase flexibility, reduce response time, and improve quality [34]. Table 1 presents the knowledge that can be captured in manufacturing operations and service at different manufacturing units. It should be noted that data generation and software support influences services and operations shown in the table.

The company itself can be considered as a manufacturing unit, which provides services and operations of product order and supply chain management. The knowledge involved in this level includes company-level planning and management rules, logics, and/or ontology. One company can have many factories with significantly different operations and attributes. At the factory level, operations include planning and management of work flow, product quality, resource allocation, and production planning, based on the company's operations. Knowledge on the factory level can include work flow, quality, resource, production-planning rules, and ontologies for developing a factory model. There can be many production lines in a factory to produce similar products as well as variations of a product, e.g., at the feature level. At the production line level, operations within a product line includes job dispatching, line balancing, and quality control. Knowledge includes production-control rules and predictive models of production lines. Many workstations comprise a production line. At the workstation level, operations can be job (in a work order) execution, machine coordination, and inspection of work in progress and final products. A workstation consists of many machines. At the machine level, operations include machine motion programming, setup planning, and measurement/inspection planning. Knowledge at this level involves process planning rules, machine capability ontology, and machine-selection rules. One level below machine is the kit level. A kit is a container with materials, parts, fixtures, tools that are used for production (machining or assembly). At the kit level, operations include kit preparation, material, tool, fixture handling, sensor selection, and labor-skill selection. Knowledge includes material, part/component, and labor-skill ontologies and their selection rules. The knowledge so far described is used by manufacturing applications for users to make decisions. Manufacturing-related data has to be available to support the use of knowledge by the software.

From a broad perspective, modeling individual knowledge constructs associated with different levels of the organization could present improvement opportunities in different enterprise units, including better hardware integration, more resilient supply chains, more flexible production systems, and improved design-to-manufacturing communication and understanding. In the next section, the concept of building a knowledge construct is demonstrated based on a real-world machining operation of a test part.

### 3.4 Case Study

The case study in this section provides an example of the role of knowledge management in smart manufacturing systems. Throughout the case study, the machining operations on a test part are considered. All data is available on the Smart Manufacturing Systems (SMS) Testbed homepage (http://smstestbed.nist.gov). More information on the test part is presented below in Section 3.4.1.

The lifecycle stages as defined for this paper are as follows. Note that this example abides by the same definition of the lifecycle described in Hedberg et al. [39].

***As-designed***: This stage includes all design information and knowledge captured in part geometry, assembly requirements, and other information traditionally captured in CAD representations (e.g., tolerances, goodness-of-fit, surface roughness, design intent, material selection, and functional design).

***As-planned***: This stage encompasses all planning rules and coding procedures (e.g., STEP-NC, G-Code, and DMIS-Code [40]) necessary to execute the build specific to manufacturing assets, including machining centers, assembly sequence, detailed process plans, and labor requirements. Process planning knowledge of interest

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includes machining and measuring equipment selection, machining strategy, inspection/measurement strategy, and measured data analysis methods selection.

***As-executed***: This stage signifies all data that describes the actual build event in the manufacturing environment. This includes but is not limited to streaming data from sensors (e.g. MTConnect-based), environmental conditions, actual material use, and operator hours. Often, this data is highly unstructured and significant data parsing and mapping is required to make sense of it.

***As-inspected***: Data collected at this stage is centered around quality assurance and performance measurement. Here, it is suggested to collect quality-based information via the Quality Information Framework (QIF) standard [41]. Knowledge of interest in inspection includes data analysis methods selection, inspection/measurement results reporting formats selection, and statistical data analysis methods selection.

In this case study, selected types of knowledge derived from the test part are captured throughout its lifecycle. It should be noted that product use, maintenance and end-of-life scenarios were not considered within this case study. In other words, the case study focuses on the four stages listed above: as-designed, as-planned, as-executed, and as-inspected.

**3.4.1 Design of Study—**The heat sink part, illustrated in Figure 5, represents a heat sink for power electronics components in an aerospace-based application. The purpose of the case study was to reflect on real manufacturing (as-executed) data to suggest changes with the planning procedure of a design. To mimic industry practice, the solid model of the heat sink part was created using Siemens's NX CAD™ software. Then, the G-code for the part build was generated through Mastercam. This information was then passed to a machinist to build the part using a GF MIKRON HPM600U, a 5-axis simultaneous milling center. The machining center resides in the NIST Smart Manufacturing Systems Testbed (machining centers are run by the NIST Fabrication Technology Office which primarily serves as a custom-job shop for NIST researchers). All data was collected via the MTConnect standard, including tool change information, feed rates, and spindle speeds. All MTConnect data was transmitted using MTConnect adapters and passed through a server via an MTConnect agent. To generate quality-related (or as-inspected) data, the native CAD file was imported into Mitutuyo's MiCAT Planner, wherein a point cloud was measured to generate simulated QIF data [42].

It should be noted that the front and back faces of the part were treated as separate builds. Only the top face (shown in Figure 6) was used for this case study.

**3.4.2 Relating Multiple Lifecycle Stages—**The MTConnect data was collected from the build and mapped back to the original solid model of the part. Observed data from the machine was then compared with the simulated (or as-planned) G-code. Therein, significant differences were observed between the as-planned and as-executed data. The plots in Figure 6 present the position of the tool with respect to the overall timeline of the part build. The top graph corresponds to the actual (or measured) build, while the bottom relates to the simulated build. All anomalous idle time intervals along with all data representing tool changes were removed. The tool changes and idle time accounted for about 250 seconds and

80 seconds, respectively, in the actual machining process. Since the time required for tool changes was not accounted for in the simulated run, it was necessary to clean the data to make fair comparisons.

Even after removing time intervals due to tool changes and idle time, the runtime of the simulated run (bottom plot) is much shorter than the actual run, measured through the MTConnect adapter. The dichotomy between the simulated and actual data presents an unexpected situation, wherein capturing knowledge could aid in the future when a similar scenario arises.

There could be many reasons as to why the actual cycle time is significantly different than simulated. In this test case, the focus was on the highlighted region in Figure 7. The 80s and 15s time intervals (in red boxes) in two graphs relate to the highlighted feature (in red) on the solid model, or the angular fins. As illustrated, the simulated run associated with the angular fins was about 15s, which significantly deviates from the actual build (lasting 80s). It is evident that the operator chose to override the original G-code at the region of the angular fins to ensure part quality, i.e., to meet the specifications of surface roughness. This realization uncovers opportunity for knowledge capture to ensure better time and cost estimation of similar processes in the future.

In the next section, other possible knowledge constructs that can be extracted from the production of the test part are summarized. Then, an instantiated knowledge artifact is shown using the angular fin milling as an example of a posteriori knowledge.

**3.4.3 Instantiating the Knowledge Object—**Figure 7 presents a summary of the data and information generated by the machining case study. The figure categorizes data, information, and knowledge into the studied lifecycle phases: as-designed, as-planned, as-executed, and as-inspected. Here, it is demonstrated how multiple lifecycle entities from different stages can be combined to generate process knowledge. These data are categorized into four main pillars corresponding to the lifecycle stages studied, including as-designed, as-planned, as-executed, and as-inspected. From the data layer, which is populated by raw data from different software systems, information can be derived that can contribute to knowledge artifacts.

The knowledge construct is created to capture product and manufacturing information (PMI) from different stages of the component's lifecycle. Here, the knowledge construct is instantiated based on the production data from the case study. The instantiated knowledge construct presents a method to link the inspection data back to design decisions. Beforehand, this understanding was encapsulated within the operator's experience. Here, the modified feed rate that was learned from the as-executed aspect of the artifact was captured as a posteriori knowledge. To make a similar feature moving forward, the as-planned feed rate will be informed by this knowledge construct, as shown in Figure 8[3].

[3]A similar analysis can be found in http://www.systems-thinking.org/cko/guide.htm

This example demonstrates not only the importance of capturing knowledge from different stages of the lifecycle but also provides a clear case wherein understanding of operator's decisions can better reflect onto the planning phase of the part build.

## 4. DISCUSSION AND IMPLICATIONS

A recent workshop investigated using manufacturing knowledge earlier in the product lifecycle and identified ten socio-technical[4] barriers to knowledge sharing [9]. Hedberg et al. 2016 [9] went on to propose several research directions for addressing the barriers to knowledge sharing – one proposed direction was to create dynamic knowledge bases. Data-driven techniques to automatically and dynamically generate knowledge bases require linking several data sources from across the product lifecycle. The concept discussed here begins to address the identified barriers. The paper proposed a concept for linking together traditionally disconnected data sources for the purposes of generating knowledge. The case study described above illustrated one example of how the knowledge extracted from data can be used to identify a mismatch between simulated and actual feed rates in a machining process and then determine a cause for the mismatch for potential part quality improvement. That example demonstrates knowledge reuse within a single lifecycle phase.

Extracted knowledge from data in several lifecycle phases would support better decision making in each phase of the product lifecycle. For example, the engineering change process could be automated to assist engineers with focusing only on decisions that require human input and removing the distractions created by trivial issues. Dynamically generating knowledge for a product by linking design, manufacturing, and quality systems and then identifying opportunities for product and process-related changes to enable more efficient and effective manufacturing of the product is an example of knowledge reuse across several lifecycle phases [43].

Hedberg et al. [36] developed an example process for automated engineering change requests (ECRs). Today, ECRs are typically generated by a person who recognizes that a manufacturing or quality issue is being caused by a design defect. However, determining that a manufacturing or quality issue is being caused by a design defect is not a simple or fast process to automate. A person will typically generate a significant amount of knowledge that they can use to determine the product lifecycle phase correlation and causation of issues. But, once the decision is made to generate ECRs, the knowledge capture is limited to justifying the ECRs in a document and the capture of that knowledge is often not stored for effective future reuse.

In the example ECR process, all the rules, resources, plans, and results are represented from the various product lifecycle phases and aggregated together to generate statistical knowledge to decide when a design should be changed to realize more efficient and effective product lifecycle processes. The process would use supervised machine learning methods to capture knowledge for future reuse by the system. Therefore, knowledge would be readily available to the system for statistically analyzing anomalies and when new knowledge is

[4]Socio-technical refers to the interaction between human behaviors and infrastructure.

required, the system would ask a human to teach the system the new knowledge. The proposed knowledge methodology could support automating ECRs because it would be capable of aggregating contextual data and information from each phase of the product lifecycle to determine facts, assign causation, and suggest fixes. In this case, the rules, resources, plans, and results from the as-design, as-planned, as-executed, and as-inspected data could be brought together to complete the workflow.

The paper describes a data-driven application supported by linked data from across the product lifecycle, which may be described as the “digital thread.” The digital thread is a way for different systems in an enterprise to all follow the same knowledge constructs. Deviations are caught automatically, which ensures that the end product is the same as the original design specification. Data is disconnected today. Each phase of the lifecycle has data that is separated from other data in the lifecycle. As a result, NIST efforts aim to deliver methods that create a digital thread of information that would be curated, made discoverable by others that could use the information, and then be observable and reusable for increasing efficiencies and product quality.

## 5. CONCLUSIONS

This paper proposed a methodology for managing manufacturing knowledge in a factory. Within this methodology, a comprehensive set of fundamental architectural elements was identified to address the knowledge interoperability barrier in smart manufacturing. Advancements in knowledge base architectures will enable knowledge integration that cuts across product design, process planning, in-process measurement, production scheduling, process control, and quality assurance in smart manufacturing.

Section 3 provided three major new components in knowledge management for smart manufacturing: (1) a general context of knowledge in relations to data, information, understanding, and autonomy, (2) knowledge constructs in a breakdown of knowledge into basic units, and (3) applications to smart manufacturing. These are necessary to methodically identify the knowledge components and their relationships under a specific context. Once these components and relationships have been identified, domain-specific knowledge development is the next logical step. More approaches for standardized representations and effective evaluations are needed specifically for manufacturing, supply chain management, and lifecycle assessment. The idea of the case study was to incorporate a variety of the lifecycle stages, including as-designed, as-planned, as-executed, and as-inspected, to reflect the challenges associated with managing data at multiple stages, as well as to illustrate how to build a knowledge construct.

Future work needs to develop more case studies to demonstrate the reuse of such knowledge constructs and the usefulness of a smart manufacturing knowledge base. To realize vast dissemination of the knowledge management methodology, it is crucial to store a wide variety and large number of knowledge artifacts. Ongoing research will investigate appropriate methods to merge knowledge constructs for reuse in different scenarios, for example, design changes, process plan updates, and new manufacturing capability selection. Given the proposed methodology, knowledge constructs could be developed for company-specific application domains. One such opportunity is the development of quality assurance describing and communicating quality information during manufacturing processes. Establishing procedures for the structured, objective representation and communication of domain-specific knowledge is essential to facilitating smart manufacturing. We learned what types of knowledge should be declared pre-process, knowledge to extract in-process, and new knowledge to learn post-process for developing knowledge constructs. NIST is seeking partners to collaborate with them to implement the demonstrated the methodology within multi-level enterprises. This could include developing individual knowledge constructs from different stages of the lifecycle and demonstrating opportunity identification for specific business goals.

## NOMENCLATURE

| | |
|---|---|
| **CAD** | Computer Aided Design |
| **CMM** | Coordinate Measuring Machine |
| **CPS** | Cyber-Physical Systems |
| **ECR** | Engineering Change Request |
| **KDDML** | Knowledge Discovery and Data Mining Markup Language |
| **KQML** | Knowledge Query and Manipulation Language |
| **NIST** | National Institute of Standards & Technology |
| **PLM** | Product Lifecycle Management |
| **PMI** | Product and Manufacturing Information |
| **PMML** | Predictive Model Markup Language |
| **QIF** | Quality Information Framework |
| **SM** | Smart Manufacturing |
| **SMS** | Smart Manufacturing Systems |
| **SOA** | Service-Oriented Architecture |
| **SysML** | Systems Modeling Language |

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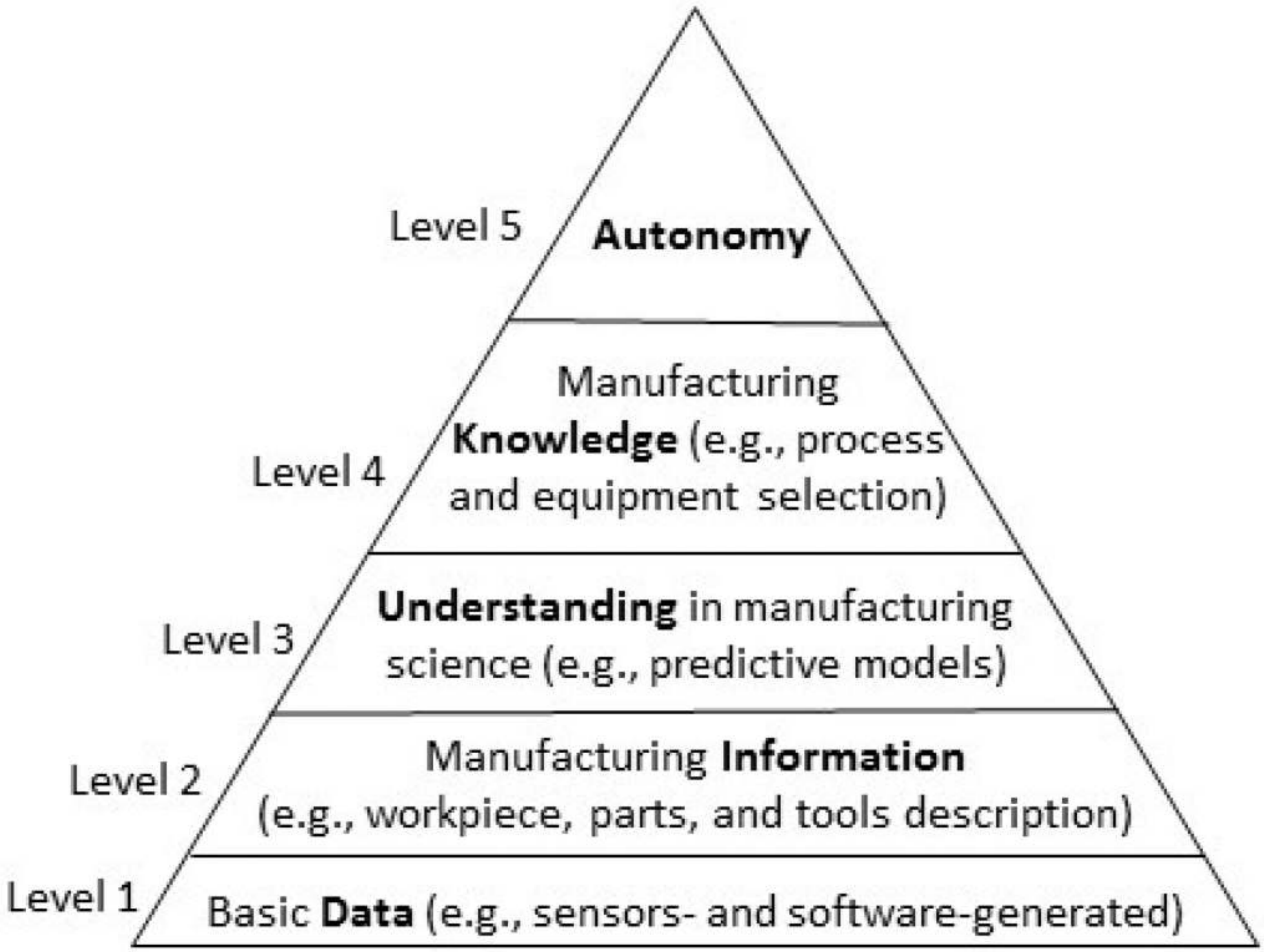


**Figure 1.**
Levels in smart manufacturing knowledge management

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level of context

| | Smart Manufacturing Application | Example |
|---|---|---|
| Autonomy | Applying knowledge for adaptation | Adaptation for new design requirements, process plan, equipment, and operator skills |
| Knowledge | Extracting manufacturing knowledge from data and science-based models | The manufacturing science of the process and system |
| Understanding | Understanding the manufacturing science | Science-based models |
| Information | Organizing/processing data to describe objects or physical phenomena | Part variation assessment |
| Data | Retrieving sensor/measurement data | Manufactured part measurement |

**Figure 2.**
Example of knowledge creation in the context of quality assurance

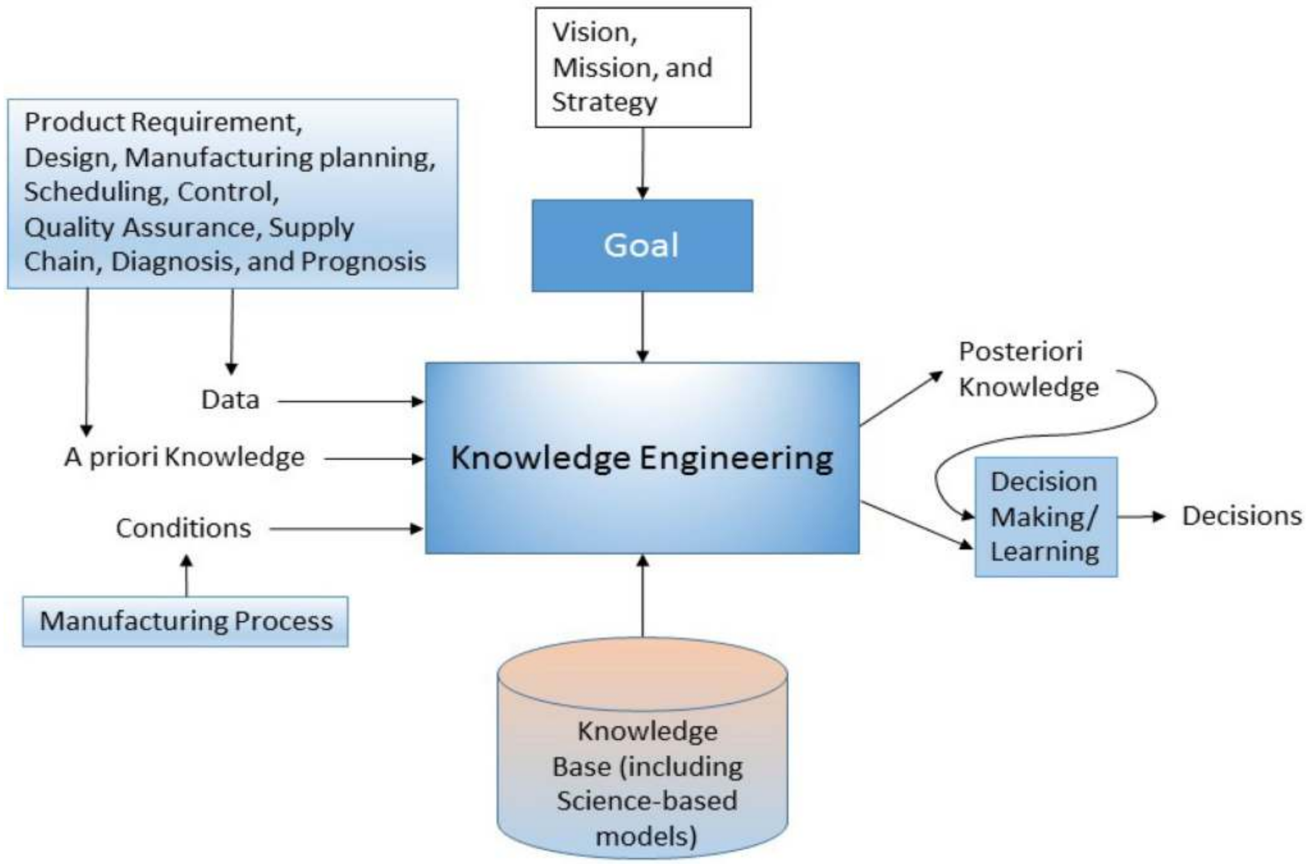


**Figure 3.**
Knowledge engineering context

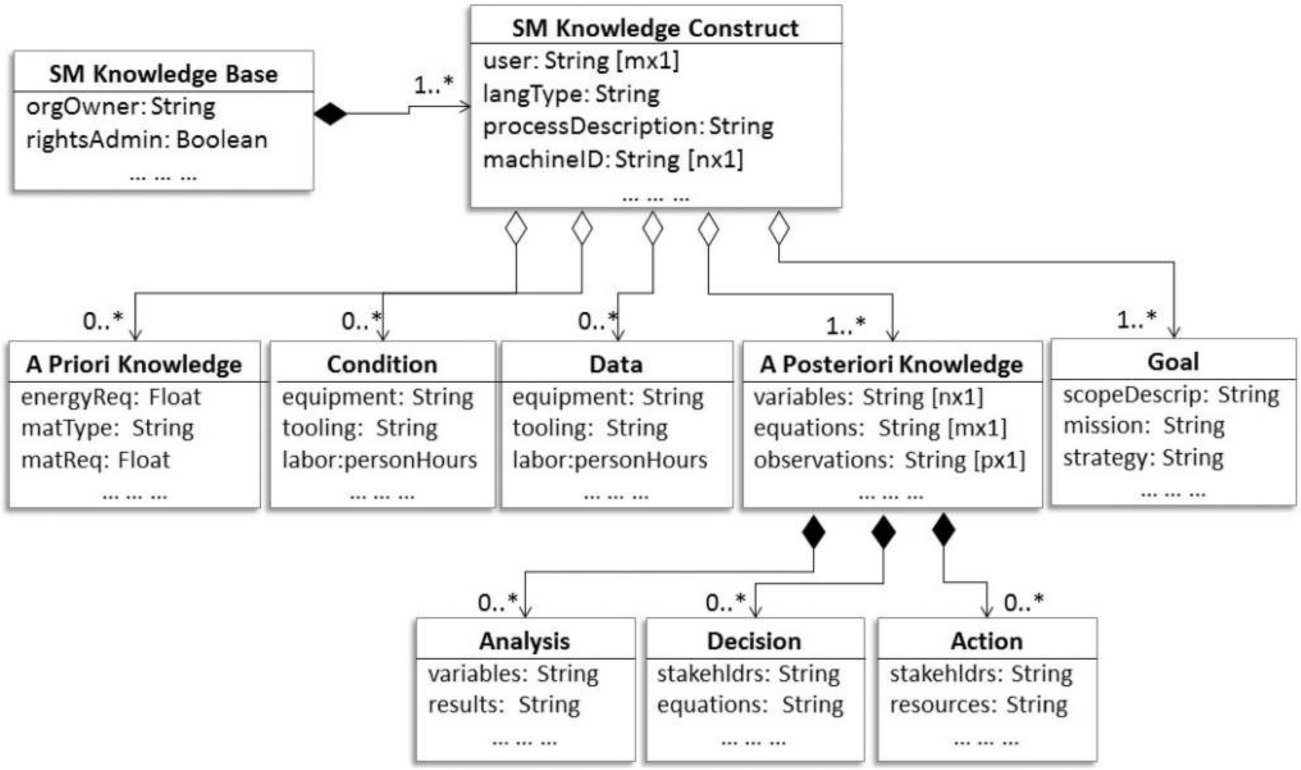


**Figure 4.**
UML depiction of a smart manufacturing knowledge construct

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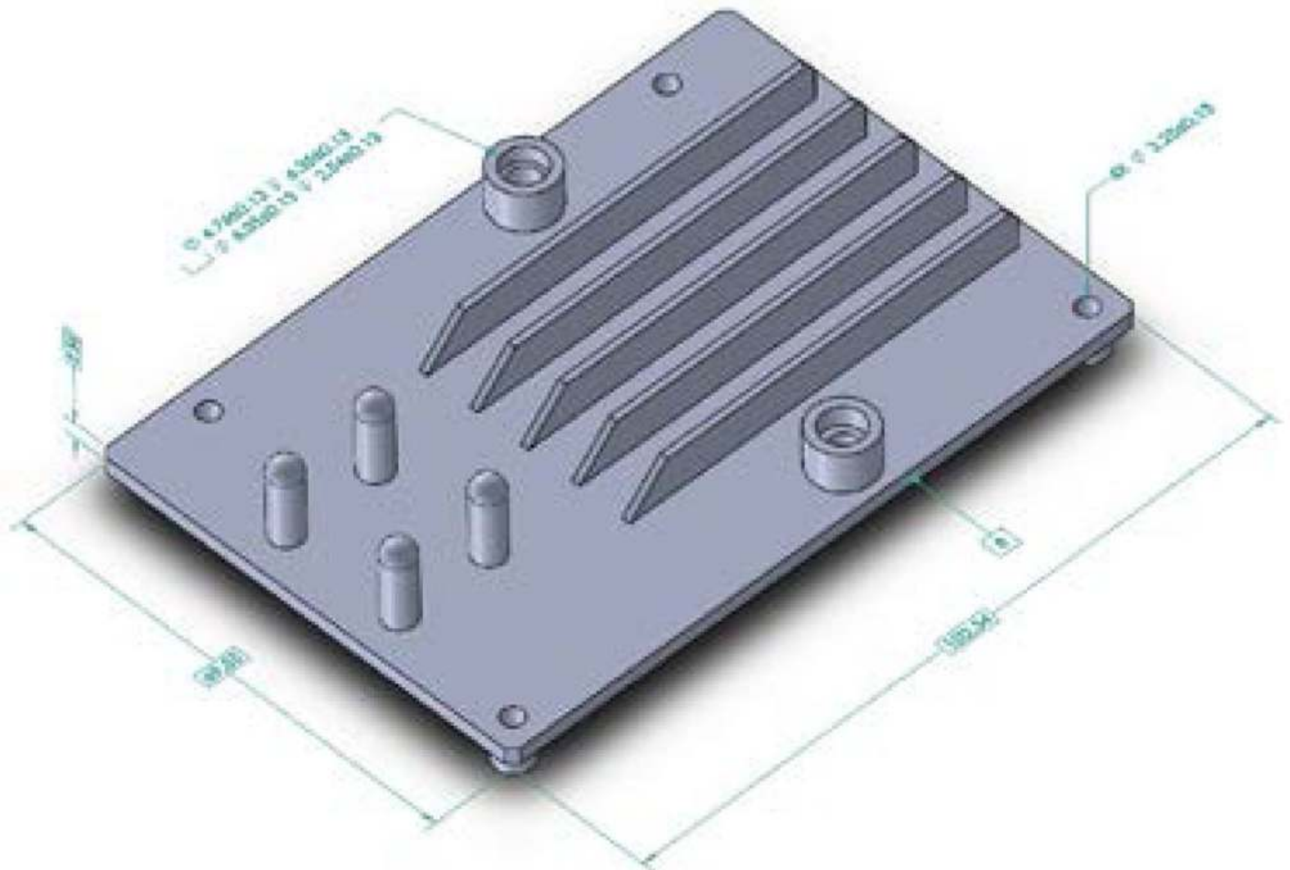

**Figure 5.**
Heat sink part: solid model of the test part used in the case study.

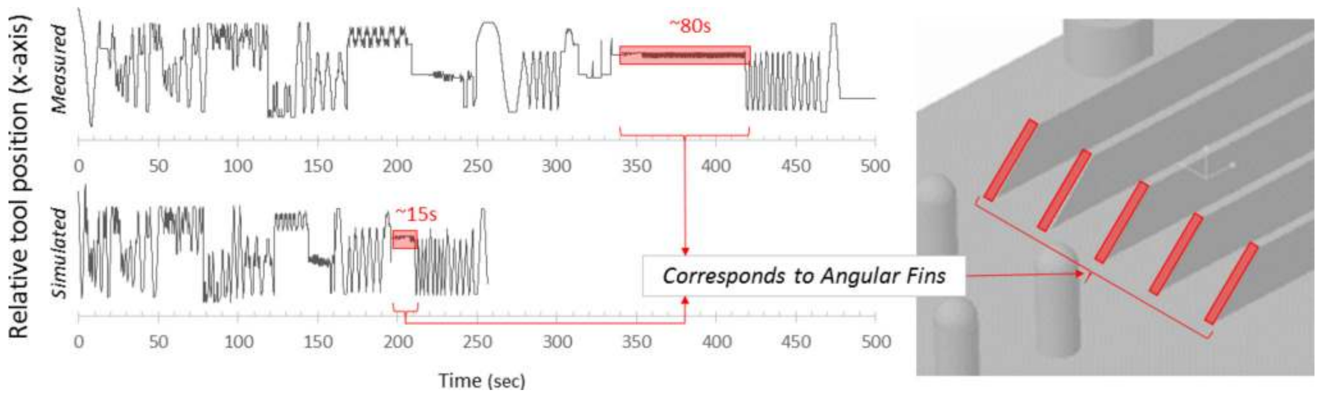


**Figure 6.**

Comparison of simulated data for part build generated by Mastercam compared to actual machine data. Note: The X-position of each dataset has been translated for ease of comparison. The vertical scales are consistent with both datasets.

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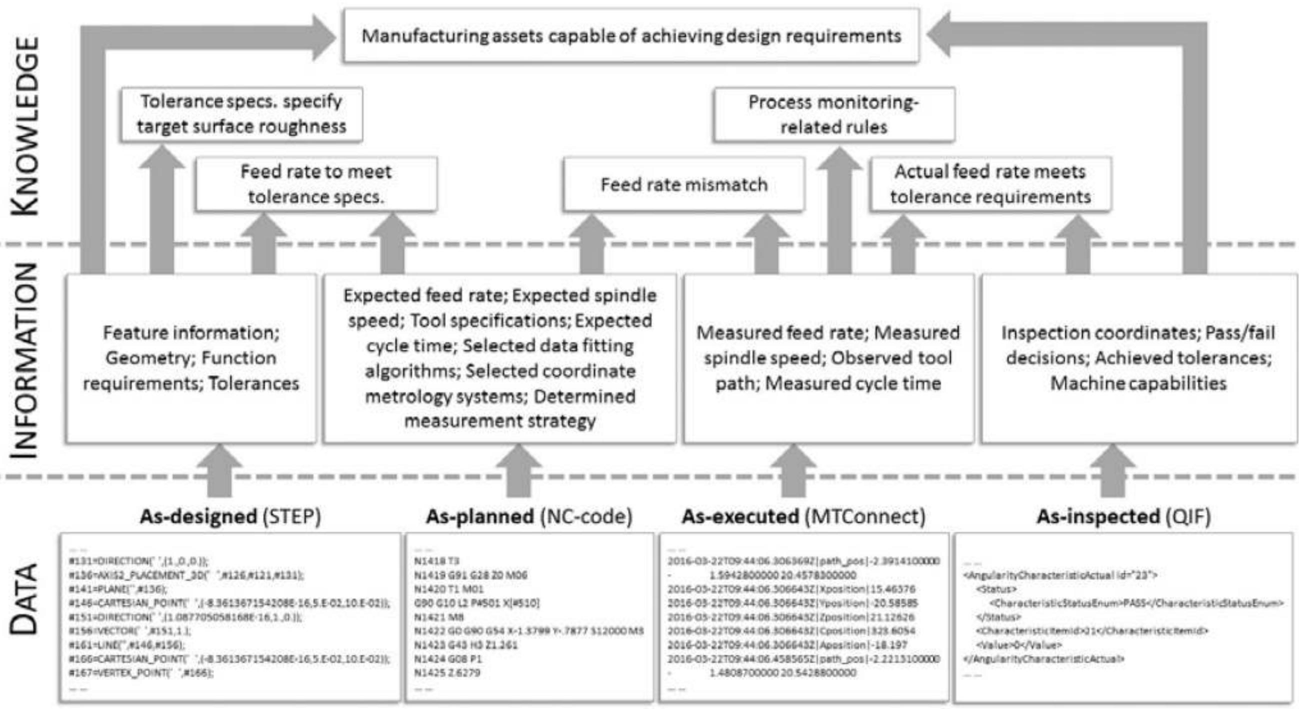


**Figure 7.**

Summary of data and information flow to create knowledge constructs relevant for producing the test part

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**Description of problem:** A heat sink was designed and planned to certain specifications of surface roughness and tolerance. The simulated run of the build specified that the part was to be cut within 250 seconds. The total machining process required nearly 900 seconds, which drastically affected the expected cycle time of the part. It was discovered that the simulated feed rate had not matched the as-executed feed rate, particularly in the complex design features of the product. To improve prediction models of throughout and quality achievement, the corrected feed rate should be captured.

**Fact**: Heat sink part with design information was provided

**Fact**: Simulated run specifies cycle time of about 250s

**Fact**: Actual throughput was 900s

**Symptom**: High cycle time

**Cause**: Data at angular fins showed significant difference

**Cause**: Simulated feed rate was higher than actual

**Fix**: Actual feed rate should be tagged to special feature and reflect real-world builds

**Figure 8.**

Example of a posteriori knowledge

**Table 1**

Example of knowledge across manufacturing units and levels

| **Manufacturing Unit** | **Service/operation (data generation)** | **Knowledge** |
| --- | --- | --- |
| Factory | Order, workflow, and quality management, resource planning, and production scheduling | Workflow management and planning rules, ontology, and constitutional logic |
| Production line | Job dispatching, line balancing, and quality control | Control rules and predictive models |
| Workstation | Work order execution, machine coordination, and inspection | Sensing, measurement rules, and statistical data |
| Machine | Machine programming, setup planning, and measurement planning | Production process model/ontology, machine capability ontology, and machine selection rules |
| Kit (material, part, fixture, tool), sensors, and labor | Kit preparation, material handling, fixture design, Sensor selection, and labor skill selection | Kit, material, component/part, and Labor skill ontologies, selection rules |