Contextualising manufacturing data for lifecycle decision-making

William Z. Bernstein*, Thomas D. Hedberg Jr., Moneer Helu and Allison Barnard Feeney

Engineering Laboratory,
National Institute of Standards and Technology,
Gaithersburg, MD, USA
Email: wzb@nist.gov
Email: tdh1@nist.gov
Email: mmh@nist.gov
Email: abf@nist.gov
*Corresponding author

Abstract: Recent advances enable data from manufacturing systems to be captured and contextualised relative to other phases of the product lifecycle, a necessary step toward understanding system behaviour and satisfying traceability requirements. Significant challenges remain for integrating information across the lifecycle and enabling efficient decision-making. In this paper, we explore opportunities for mapping standard data representations, such as the Standard for the Exchange of Product Data (STEP), MTConnect, and the Quality Information Framework (QIF) to integrate information silos existing across the lifecycle. To demonstrate this vision, we describe a reference implementation with a contract manufacturer in the National Institute of Standards and Technology (NIST) Smart Manufacturing Systems Test Bed. Using this implementation, we explore how knowledge generated from manufacturing can support lifecycle decision-making. As a case study, we then present an interactive prototype correlating the test bed's data based on the context that must be provided for a specific decision-making viewpoint.

Keywords: digital thread; knowledge management; product lifecycle management; smart manufacturing; lifecycle decision-making; manufacturing data.

Reference to this paper should be made as follows: Bernstein, W.Z., Hedberg Jr., T.D., Helu, M. and Feeney, A.B. (2017) 'Contextualising manufacturing data for lifecycle decision-making', *Int. J. Product Lifecycle Management*, Vol. 10, No. 4, pp.326–347.

Biographical notes: William Z. Bernstein is a Mechanical Engineer in the Life Cycle Engineering Group at the Systems Integration Division, Engineering Laboratory, National Institute of Standards and Technology (NIST). He is developing a new visualisation laboratory at NIST to support research into smart manufacturing systems with particular emphasis on deriving actionable knowledge from manufacturing data. His work contributes to standards for manufacturing system and performance characterisation and the integration of manufacturing and design knowledge to connect the 'digital thread' between these two areas.

Thomas D. Hedberg Jr. is a member of the Systems Engineering group at the Systems Integration Division, Engineering Laboratory, National Institute of Standards and Technology (NIST). At NIST, He is the project leader of the digital thread for smart manufacturing project in the smart manufacturing operations planning and control program and the co-Coordinator of the Smart Manufacturing Systems Test Bed. He is a voting member of the American Society of Mechanical Engineers (ASME) Y14.37, Y14.41, and Y14.41.1 subcommittees and co-Chair and Americas Lead for the Visualization Working Group for LOTAR International.

Moneer Helu is a Mechanical Engineer in the Information Modeling and Testing Group at the Systems Integration Division (SID), Engineering Laboratory (EL), National Institute of Standards and Technology (NIST). His research at the NIST is primarily in the areas of prognostics and diagnostics for smart manufacturing systems. He has been recognised by the Society of Manufacturing Engineers (SME) in the 2014 list of the *30 Under 30: Future Leaders of Manufacturing*. He is also a Research Affiliate of the International Academy for Production Engineering (CIRP).

Allison Barnard Feeney leads the Systems Engineering Group under the Systems Integration Division of the Engineering Lab (EL), National Institute of Standards and Technology (NIST). She also manages EL's Smart Manufacturing Operations Planning and Control program. She has worked in manufacturing standards implementation, conformance testing, product data standards, and systems integration throughout her NIST career. She is a past recipient of a Department of Commerce Silver Medal, PDES, Inc.'s Bryan K. Martin Technical Excellence Award, PDES, Inc.'s Brad Ridgon Technical Management Award, and the NIST Edward Bennet Rosa Award.

1 Introduction

With the emergence of the internet of things (IoT) in product lifecycle management (PLM), harnessing knowledge generated by engineering processes has become a primary goal. According to a report by McKinsey Global Institute, the manufacturing sector "stores more data than any other sector – close to 2 exabytes of new data stored in 2010" (Manyika et al., 2011). However, it is widely accepted that until now, manufacturing has been far from meeting its true potential in the digital age (Lee et al., 2013).

A number of challenges impede the aerospace industry from harnessing lifecycle data to make informed decisions. One challenge is that ongoing research and development efforts have been occurring in silos (in a single lifecycle phase) with little to no relation to and compatibility with other lifecycle phases. In manufacturing operations, this is evidenced by difficulties relating design information, e.g., Standard for the Exchange of Product Data (STEP), machine instructions, e.g., NC-code, real-time machine performance, e.g., MTConnect, and inspection results, e.g., Quality Information Framework (QIF).

It is well-accepted that approximately 70% of the total cost of a product's development is committed in the design phase (Ullman, 2010). Hence, developing appropriate knowledge-based models that project downstream information, such as the standard information models mentioned above, to the design phase has significant potential for enterprises. In addressing these opportunities, this paper:

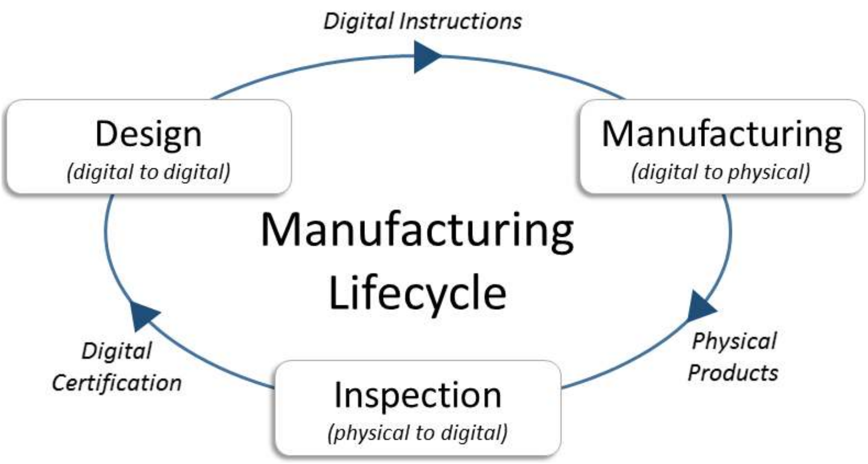
1. details appropriate contextualisation at different stages of the lifecycle
2. presents a reference implementation that enables correlation of design, planning, manufacturing, and inspection data as well as an interactive prototype of this implementation that is applied to a case study analysing the production of an avionics heat sink part
3. identifies key open research questions and challenges.

Through our research, we demonstrate opportunities for linking, or 'threading', stages of the lifecycle together, as well as for improving the overall decision-making workflow.

2 Background

Figure 1 presents the portion of the lifecycle that is the focus of this paper; we call this portion the manufacturing lifecycle. It encompasses the design, manufacturing, and inspection activities. Here, we show a simplified perspective of the data transfer among the lifecycle stages. Design transforms digitally-based customer requirements into actionable specifications, including geometry, material, and finish specifications. The manufacturing phase converts digital instructions into physical products, including waste material. The inspection stage then transforms physical product information into digital measurements to compare against the original design instructions. In this subsection, we review the as-is workflow and decision-making within the manufacturing lifecycle. We discuss decisions used in selecting the project to pursue, appropriate management of the product lifecycle, and finally the influence imparted on the lifecycle by decisions.

Figure 1 Manufacturing lifecycle with simplified description of data transfer between each lifecycle stage (see online version for colours)



2.1 As-is decision-making workflow in aerospace manufacturing

Many characteristics of aerospace manufacturing, such as low batch sizes and stringent geometric requirements, present unique challenges to efforts to improve the existing workflow. In this section, we review existing frameworks for PLM. This perspective reveals research opportunities for contextualising lifecycle data for better decision-making.

2.1.1 Project selection

One of the first decisions in the product lifecycle of an aerospace project is to determine if the project should be undertaken. There are several factors that an organisation may use to decide to pursue a project, such as cost, return on investment, competitive advantage, and/or customer requirements. However, there is no standard process for determining how to decide to undertake a project. Literature from the management domain (Liu and Leitner, 2012; Parrino et al., 2005; Smith, 2007) provides recommendations and tools to assist the decision-making process, but these are simply rules-of-thumb that require subjective review with a broad multi-domain expertise by the decision maker.

Aerospace organisations adopted the Six Sigma methodology to bring more rigor to project selection and execution. Six Sigma's define, measure, analyse, improve, control (DMAIC) approach was the start of a formal method for project execution in an effort to control the quality of the product and related processes. To further assist in the decision to pursue a project, organisations couple Six Sigma principles with tools such as Pareto priority index (PPI), project assessment matrix, analytic hierarchy process (AHP), quality function deployment (QFD), and voice of customer (VOC). While all of this brings a more formal method to the decision-making process for project pursuits, the decision inputs are still subjective, require data and expertise from multiple domains, and are at risk of being influenced implicitly and/or explicitly by the decision maker's biases.

Dinesh Kumar et al. (2007) proposed applying data envelopment analysis (DEA) to Six Sigma project selection. DEA is an objective, linear-programming-based method for identifying empirical production functions. DEA is built upon macroeconomic theory. The method compares all units in a population on many dimensions simultaneously to assist in identifying the empirical frontier. DEA in project selection serves as a way to identify the projects that are more likely to result in the maximum benefit. However, collecting sufficient data to complete the DEA remains a challenge. The DEA method classifies important inputs and outputs for Six Sigma projects. The inputs can be further categorised into three categories as proposed by Pande et al. (2014):

1 business benefits criteria

2 feasibility criteria

3 organisation impact criteria.

DEA remains one of the only proposals for formalising an objective decision-making approach in deciding to pursue a project.

In practice, it remains a challenge to truly assess a project's quality and viability in its early stages. Unexplored opportunities exist in empowering decision-making for project selection through empirical historical data. Rather than relying on forecasting models riddled with uncertainty, industry can learn from successes of past projects that exhibit similar paths and attributes to those proposed. Connecting data across the lifecycle will enable such innovation.

2.1.2 Lifecycle management

After project selection, aerospace organisations typically implement a stage-gate (Cooper, 2001) or waterfall project management approach. Cooper (2001) developed his stage-gate model (shown at the top of Figure 2) to support the success of product innovation through the effective and efficient management of the lifecycle process. Cooper's model breaks a project into five stages requiring the passage of a gate before proceeding to the next stage. The gates provide quality control to the process by incorporating go/no-go decisions at strategic points in the process (Cooper, 2001). The waterfall method is similar to the stage-gate model. Other product development methods, such as the modified waterfall and spiral model, provide varying degrees of specificity and are appropriate depending on domain and context (Munassar and Govardhan, 2010). These traditional approaches are popular with aerospace organisations because the phased approach with formal approvals is effective in limiting scope creep (Moss and Atre, 2003).

Aerospace products are capital intensive due to long manufacturing lifecycles and significant regulatory oversight. The break-even and/or return-on-investment points for aerospace products often lie several years into the product lifecycle (Buxton et al., 2006). Aerospace organisations want to shorten the development cycle time. However, shortening the cycle time merely compresses the same number of decisions into a much shorter time frame (Johansson et al., 2011). Recent research has suggested either improving the ability to make the right decisions the first time and avoid iterations or supporting failing early and often to enable success sooner (Kelley and Littman, 2001; Schrage, 2000; Thomke, 2001). These strategies increase the risk of decreased quality in the process and product, the opposite of Six Sigma's original intent. In the end, aerospace organisations are forced to make decisions earlier using preliminary data and uncertain assumptions instead of established facts (Johansson et al., 2011).

Cooper (2001) recommended representing all critical roles in a product-development team from the start of the process. This would improve earlier decisions by ensuring the appropriate expertise and knowledge is available at the time of the decision-making. Cooper (2001) suggested there are two ways to succeed with products:

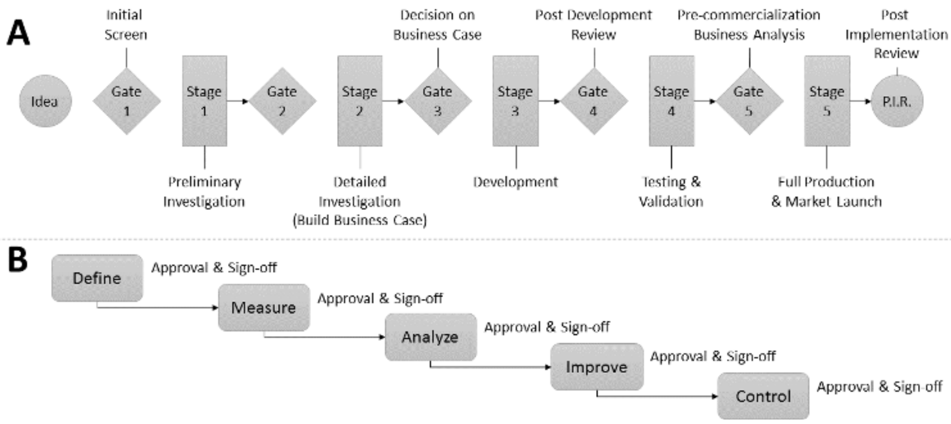
1 doing projects right

2 doing the right projects.

We discussed 'doing the right projects' in the previous subsection. 'Doing projects right' requires a process that follows commonly accepted management guides. These guides include using teams effectively, doing up-front research before starting development, analysing the voice of the customer, and ensuring a stable product definition prior to deployment or launch (Cooper, 2001). Therefore, doing projects right requires a certain level of knowledge maturity.

While the stage-gate model and the waterfall approach both provide a good foundation for managing product-development activities, they may fall susceptible to a lack of cross-domain understanding of types of information that force change to occur during activities – specifically, when changes occur as a result of requirement changes. This opens up both the stage-gate and waterfall processes to the risk of continuing to mature projects that are no longer the right projects. Recently, standards development have begun to focus on defining processes involved in the lifecycle independently from the stage in which they are applied, e.g., ISO 15288 (ISO/IEC/IEEE 15288:2015, 2015). However, these efforts remain in a nascent stage.

Figure 2 Examples of the (a) stage-gate process (from Cooper, 2001) and (b) waterfall process



Note: Each process has formal times for review, approval, and sign-off before the process may continue.

2.1.3 Decision influences on the lifecycle

Regardless of where decisions are made (e.g., design, manufacturing, inspection), the major decisions happen at planned, formal times [e.g., preliminary design review (PDR), critical design review (CDR), manufacturing planning sign-off]. Minor decisions are rarely scrutinised in great detail. Typically, minor-decisions aggregation is only implicitly accessed during formal reviews. In addition, there is little cross-domain decision-making. Most cross-domain activity is typically a cursory review of decisions during the formal reviews. Deep reviews occur only when problems arise. Shortening of cycle time is a primary driver for the lack of cross-domain decision-making.

Several methodologies exist for the purpose of integrating the various lifecycle domains. Yet, methodologies such as integrated product and process development (IPPD), collaborative product development (CPD), Six Sigma, and design for '*x*' (DFx), often remain siloed within a respective domain because there is a lack of resources, manpower, and/or knowledge available to capture necessary data from all the domains and utilise the methods completely. Some aerospace organisations have mandated that employees be trained in Six Sigma. In particular, design organisations are pushing design for Six Sigma (DFSS). However, in reality, the DFSS process and documentation is often completed immediately prior to a formal review and approval period instead of throughout the entire design activity. This is due to practical challenges related to the lack of information and ambiguity in new designs, e.g., unknown failure modes (Gardner and Wiggs, 2013). Again, DFSS is driven by the desire to shorten the cycle time and a lack of resources to properly manage downstream processes. These factors lead to decisions being made without an understanding of how those decisions affect the remainder of the lifecycle.

The most advantageous time to make a change in a product's lifecycle is in the early stages because there is an inherent flexibility in those decisions being made (Johansson et al., 2011). Ullman (2010) states that the more one learns about a product or process, the less freedom one has to use what one knows. Salado Diez (2014) shows that every decision made early in the lifecycle becomes a constraint on the remainder of the lifecycle because each subsequent decision further reduces the compliant solution space. Therefore, the best time to make large and significant decisions in the lifecycle is typically early in the design phase when the solution spaces are theoretically the largest. However, making decisions early in the lifecycle requires decision-making under uncertainty. The concepts of error mapping, error budgeting, and uncertainty quantification are well understood within the manufacturing and quality domains. The engineering analysis and simulation domain also strives to quantify uncertainty. There are active standardisation activities in this domain (Heller, 2016) for uncertainty quantification, verification, and validation of models. However, the design community is not well equipped to manage uncertainty.

Aerospace organisations typically develop procedures, policies, and guides to assist design activities. This assistance is often in the form of paper-based knowledge bases of recommendations and requirements for completing different types of designs. The time frame for updating a procedure, policy, or guideline in the aerospace industry is typically one to two years. This is in part due to the rigorous requirements related to aerospace safety set by regulatory agencies (e.g., US Federal Aviation Administration, European Aviation Safety Agency). Therefore, it is important for aerospace organisations to understand the uncertainties and ambiguities that exist in the lifecycle and to ensure decisions account for them (Johansson et al., 2011).

To move toward a better understanding of uncertainty in the lifecycle, we can ask a series of questions. What are all the known potential sources of variation? Where do those sources exist within the lifecycle? Can we quantify the uncertainty and variation? Can we aggregate those uncertainties across the lifecycle and should we? Lastly, how can we control the variations and uncertainty? To answer these questions, a certain level of knowledge maturity must be achieved. Johansson et al. (2011) proposed that achieving sufficient knowledge maturity could provide decision support that would increase a decision maker's awareness of the knowledge base. This could further support cross-domain collaborations to identify useful knowledge. For example, the design and manufacturing domains could work closely together to ensure design can take advantage of manufacturing knowledge during design activities. Hedberg et al. (2017) identified ten recommendations for using manufacturing knowledge earlier in the lifecycle, but industry needs a way to generate knowledge bases dynamically and the information requirements of the lifecycle must be better understood before these ten recommendations can be implemented.

While we understand that we will never remove all uncertainty from the lifecycle, especially in design, it is imperative that uncertainty and ambiguity related to the design process be identified effectively, efficiently, and explicitly (Stacey and Eckert, 2003). Only then would we be able to determine that we are doing the right project, doing the project right, and building an understanding of how every decision influences the remainder of the lifecycle. The potential benefits include more precise schedules, better cost controls, a solution space optimised for the entire lifecycle, and maximised quality of both the product and related processes.

2.2 PLM-focused efforts to realise the digital thread

In response to these challenges associated with better understanding data throughout the lifecycle there has been a focus over the past 20 years on developing visual exploration frameworks and interfaces targeted at the appropriate presentation of knowledge. However, the manufacturing domain has not yet fully adopted these latest interface development guidelines, such as Pirolli's information foraging theory Pirolli and Card, 1999. There have been some promising efforts in closing the gap of adoption. Hedberg et al. (2017) proposed three primary research directions to push the manufacturing domain forward:

1 developing dynamic knowledge bases

2 defining minimum information requirements

3 supporting interoperability issues.

These suggestions directly align with needs for adopting best practices and techniques from information theory.

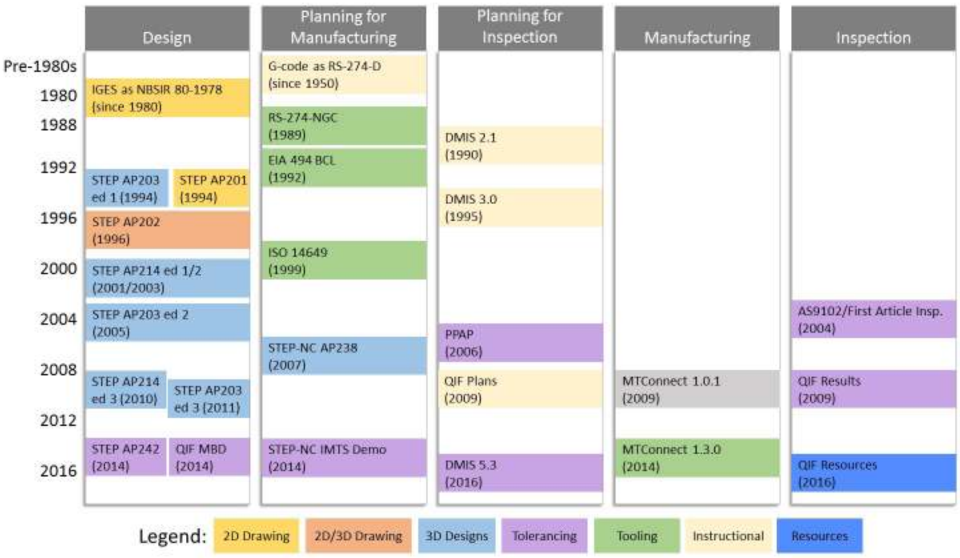
The realisation of dynamic knowledge bases in manufacturing requires formal methods for linking across legacy databases at unique stages of the lifecycle. The challenge here heavily relates to interoperability issues, not only associated with industry-used software packages (e.g., integration of multiple CAD/PDM tools) but also with the lifecycle data itself (e.g., integration of STEP and QIF data). One primary research focus in relating different manufacturing data representations is improving decision-making pipelines for finely tuning computer numerically controlled (CNC) machines (Xu and Newman, 2006). For example, Campos and Hardwick (2006) proposed a standards-based method for training information across CNC manufacturing.

Another key challenge is the diversity in roles and perspectives of stakeholders, or the primary consumers of lifecycle data. Presenting on-demand, consumable lifecycle data at different points in the lifecycle requires a new information model that supports the minimum amount of information for a variety of scenarios. A similar research opportunity was identified in the bioinformatics community at the onset of the human genome project. Le Novère et al. (2005) proposed a minimum information model (MIM) for the purpose of biochemical model reuse in drug design simulation. Similarly, Smith et al. (2007) presented an upper ontology to support biomedical data integration, including all necessary governance and verification protocols.

As with the medical community, manufacturing requires a coalescence of lifecycle perspectives and requirements to identify a similar common information model. According to a recent survey of engineering-based industry, most manufacturers perceive model-based enterprise (MBE) activities as helpful but find its current practice too costly to fully implement in terms of both resources and time (Ruemler et al., 2017). As a result, many of the ongoing efforts in industry have focused on developing platforms. Examples of projects related to capturing physical information in digital form include GE's Predix (https://www.ge.com/digital/predix) and Siemens Mind Sphere (http://www.siemens.com/global/en/home/company/topic-areas/digitalization/mindsphere.html) platforms.

Currently, the focus of these efforts is on the creation of a digital twin of what is happening in the physical world, i.e., on the manufacturing floor in both of these examples. One key value proposition of these efforts is the ability to predict breakdowns and proactively maintain machines. Derhamy et al. (2015) categorise key commercial software available for implementing IoT infrastructure, including tools such as Xively (https://www.xively.com/), ThingWorx (https://www.thingworx.com/), AllJoyn (https://allseenalliance.org/framework), and Arrowhead (http://www.arrowhead.eu/). These frameworks aim to provide necessary infrastructure agnostic of application domain for implementing IoT. It is clear that choosing the right technology for the right domain is critical to ensure success. To help bridge the gap between these technologies and manufacturing, commercial CAE software has begun to provide IoT driven use cases for decision-making. Waurzyniak (2013) reports several commercial efforts, highlighting Siemens's HD-PLM (http://www.lifecycleinsights.com/technology-providers/hd-plm-siemens-plm/), Dassault Systémes's Delmia brand (https://www.3ds.com/products-services/delmia/), and AutodeskPLM 360 suite (https://a360.autodesk.com/). Each of these platforms help address specific use cases, yet a unified, fundamental infrastructure for such software to communicate across one another is absent.

Figure 3 Timeline-based depiction of standards work in specified lifecycle stages, including design, planning (further separated into two categories), manufacturing, and inspection (see online version for colours)



Notes: Though this figure does not incorporate all standards activities in the time horizon, it illustrates the importance of knowledge capture and projection to design in the manufacturing space. In general, these standards are mostly focused on the arrows depicted in Figure 1.

There have been a wide variety of standards specific to elements of smart manufacturing. These efforts are vital for the implementation of the ongoing research efforts described above. To maximise the flexibility and responsiveness of manufacturing systems, there has been a recent push toward formal standard representations of different aspects of the lifecycle, including geometric and feature-based design, process planning, process monitoring, and quality and inspection (Hedberg et al., 2016). These efforts present significant opportunities for knowledge reuse throughout the design process. If successful, the status quo of sequentially passing information, both physical and digital, as depicted in Figure 1 will fundamentally change. Ideally, information will be readily available in a consumable form related to a context appropriate for its viewer.

Figure 3 makes it clear that the advancements in the standards community occur in lifecycle 'siloes' with a variety of perspectives. As a result, it is essential to incorporate a diversity of perspectives reaching across different phases of the lifecycle in the development of advanced decision-support interfaces. The plethora of standards in this space make it challenging to coalesce a common vision across an organisation. In response, ISO 14638 (2015) provides a matrix-based method to help select appropriate standards that formalise different aspects of the product lifecycle. This method does not, however, offer techniques for formally mapping across various PLM-related standards. In other words, the diversity of PLM concepts across the lifecycle can be addressed through contextualisation. In this work, our solution focuses on manually combining data to provide a decision-making platform that caters to a variety of perspectives across the lifecycle, e.g., design, engineering, manufacturing, and inspection.

3 Contextualisation approach

The quality of the information extracted from collected data depends on the appropriateness of the context developed when curating the data. Contextualisation describes the process of combining different types of data and information to provide a full and complete perspective of a phenomenon or situation. The challenge when considering the product lifecycle (or any domain) is that many different contexts are required to address the roles, priorities, and goals of each actor within the system or domain of interest. Focusing on the delivery of product within the lifecycle, we can consider four broad categories of actors, and subsequently contexts that need to be established as described in Table 1. It should be noted, though, that the context needs for actors within each of the categories shown in Table 1 may not be uniform. For example, production and maintenance personnel in the manufacturing stage often have conflicting interests: production generates income when equipment runs whereas maintenance creates value when equipment does not run. Thus, one viewpoint of the lifecycle influences the context that must be developed to address a question or decision of interest.

No matter what viewpoint of the lifecycle we might consider, the appropriate context should enable an understanding of how some discrepancy, error, or impact relates back to the focus within the lifecycle stage (defined in Table 1). Manufacturing decisions require a curated dataset that relates some impact of interest to process-related information so that one can understand the physical reasons driving any observed variations or events. For example, if one is interested in minimising the energy consumed by a machine tool, then the measured power demand must be related back to process parameters (e.g., speed, feed, position). Similarly, design, planning, and inspection decisions require curated datasets that relate some impact of interest to information about part features, process capabilities, and characteristics, respectively.

The contextualisation that we have described focuses on viewpoints within one lifecycle stage. This specific focus is what often occurs during decision making across the lifecycle. However, we intuitively understand that many (if not all) decisions made in one lifecycle stage impact one or more other lifecycle stages. For example, a discrepancy in the manufacturing process (e.g., feedrate mismatch during machining) could be due to operator error (e.g., accidental feedrate override), poor process planning (e.g., toolpath unable to reach commanded feedrate), or inappropriate design (e.g., features that cannot be machined without feedrate mismatch). Determining the root causes of such discrepancies requires that we develop context by fusing data from design, planning, manufacturing, and inspection. This is the objective of the reference implementation that we developed in this research.

Table 1 Four broad categories of actors tasked with the delivery of product within the lifecycle with each actor's focus (the aspect of the product lifecycle that they influence) and role (the influence of the actor on the specified aspect)

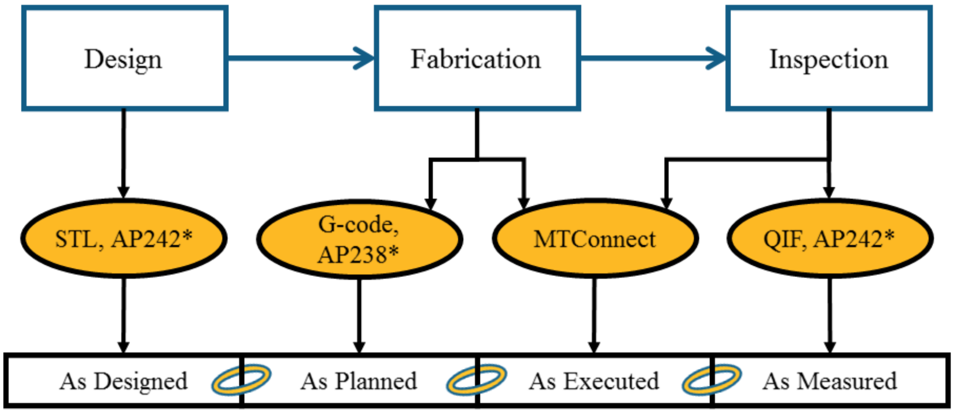
Lifecycle stage	*Broad focus*	*General role*
Design	Features	Define features – a physical portion of a part or its representation in a drawing or digital format (ASME Y14.5, 2009) – to meet requirements of form, fit, and function (i.e., purpose) of part
Planning	Capabilities	Organise a set of capabilities executed through different manufacturing processes to create features of part
Manufacturing	Processes	Implement manufacturing processes with maximum productivity to create features of part
Inspection	Characteristics	Compare characteristics – control placed on an element of a feature (DMSC, 2014) – of manufactured feature to its definition in design

3.1 Reference implementation

The challenge when attempting to fuse data from design, planning, manufacturing, and inspection is the lack of commercial solutions that enable the integration of systems across the product lifecycle. PLM solutions exist, but these are typically expensive, inaccessible for many organisations (especially small-and-medium enterprises), and focused primarily on engineering and information technology (IT) systems with little to no access to operational technology (OT) systems, such as manufacturing equipment. The goal of this research is to address the lack of commercial solutions by developing a reference implementation that integrates data from silos across the product lifecycle and that can be used by all organisations. To do so, we leverage the National Institute of Standards and Technology (NIST) Smart Manufacturing Systems (SMS) Test Bed.

The NIST SMS Test Bed has two major components: the Computer-Aided Technologies (CAx) Lab and the Manufacturing Lab. The CAx Lab focuses on IT systems for design, planning, inspection, data management, and verification and validation. The Manufacturing Lab networks the IT and OT systems of an actual contract manufacturer, including machining tools, inspection equipment, and manufacturing execution systems. The NIST SMS Test Bed provides the physical infrastructure and data needed to design, test, and demonstrate our reference implementation. Figure 4 describes the types of data collected by the NIST SMS Test Bed that may be fused by our reference implementation. It also highlights our use of existing data standards, which are necessary to fuse data from heterogeneous systems for contextualisation. Three of the data standards included in our reference implementation are STEP, MTConnect, and QIF.

Figure 4 Types of data collected, aggregated, and curated from the NIST SMS test bed (see online version for colours)



Notes: We define the lifecycle of manufacturing data into four stages: as-designed, as-planned, as-executed, and as-measured. Asterisks in the figure denote application protocols of ISO 10303.

3.1.1 Standard for the Exchange of Product Data

ISO 10303, commonly known as STEP, is an international standard designed to exchange digital information, enabling an ever-widening range of engineering software systems to interoperate (ISO 10303-1, 1994). STEP, developed through the International Organization for Standardization (ISO) by a global consortium of technical experts from industry, governments, and academia, provides a robust neutral file format that has the potential to save approximately $1 billion (in 2001 dollars) per year by reducing interoperability problems in the automobile, aerospace, and shipbuilding industries alone (Gallagher et al., 2002).

STEP is implemented through parts of the standard called application protocols. The application protocol used for representing three-dimensional (3D) design models is ISO 10303-242:2014 titled ‘Managed Model Based 3D Engineering’ (ISO 10303-242, 2014). Commonly known as AP242, this standard specifies computable representations for several types of 3D model data, including dimensional and geometric dimensioning and tolerancing (GD&T) information. This information conveys the design intent and functional requirements of the product to the manufacturing domain. The intent is for AP242 to support all product and manufacturing information (PMI) needed to communicate with manufacturing and inspection planning. A second edition of AP242 will add new representations for electrical wire harnesses, kinematics, and additional PMI (Feeney et al., 2015).

Another STEP application protocol, ISO 10303-238, or STEP NC, retains design information of a given part along with machine executable commands for its build (ISO 10303-238, 2007). STEP NC is currently being revised to update its content based on years of implementation experience and to share the architecture and underlying geometry and PMI models with STEP AP242.

3.1.2 MTConnect

MTConnect is an open-source, read-only, extensible data-exchange standard for manufacturing and was originally designed to transform process-related information from proprietary to structured-XML formats accessible for monitoring applications (MTConnect Institute, 2014). The standard is based on HTTP and provides information models and communication protocols to enhance the data-acquisition capabilities of manufacturing equipment, systems, and applications and enable a plug-and-play environment. Four information models are currently included in MTConnect: devices, streams, assets, and errors. These models are the only established common vocabulary and structure for manufacturing equipment data. The success of these models has led MTConnect to become the primary IoT manufacturing standard for several organisations, including General Electric.

In addition to it being a primary manufacturing data standard, MTConnect was selected for our reference implementation for several technical reasons. First, it provides an XML information model that is designed to integrate easily with many communication protocols. The read-only structure protects manufacturing equipment and systems that often cannot be exposed to external networks because of outdated operating systems. Finally, the agent-adapter architecture eases implementation. The agent is an HTTP server and RESTful interface (Richardson and Ruby, 2008) that implements the information model for legacy equipment and serves data to the agent. Through this architecture, we can effectively integrate different manufacturing systems and expand our data collection efforts.

3.1.3 Quality Information Framework

QIF is an ANSI-accredited standard developed by the Dimensional Metrology Standards Consortium (DMSC, 2014). The goal of the standard is to provide a normalised method in the metrology domain for information gathering and exchange. QIF is freely available via an internet download and includes eight parts (DMSC, 2014):

1 overview
2 library
3 model-based definition
4 plans
5 resources
6 rules
7 results
8 statistics.

Several use cases are covered by QIF. One is the enabling of original equipment manufacturers (OEMs) to curate and merge inspection data coming from multiple internal and external sources (e.g., QIF results, QIF statistics). Another capability of QIF is allowing OEMs to provide rules and inspection requirements to suppliers in an interoperable form that can quickly be ingested into supplier metrology systems (e.g., QIF rules). A use case for suppliers enables the gathering and sending of quality-related data (e.g., QIF plans, QIF results, QIF statistics) to the suppliers' customers. Lastly, both OEMs and suppliers can represent and share their available dimensional-metrology-equipment (DME) resources (e.g., calipers, micrometers, coordinate-measurement machines) to enable quicker inspection planning and analysis (e.g., QIF rules, QIF resources).

QIF includes normalised XML schema definitions for each part of the standard. This could simplify the integration with MTConnect and other technologies to enable a holistic analysis of the lifecycle. We used the standard to enable coverage of the quality-domain portion of the product lifecycle. We view quality data as the link between the cyberspace and physical-space. Using QIF to gather quality information in a standard form supports the linking and observation of the two spaces by using measurement and analysis of the transformations from digital product definitions to physical parts (Hedberg et al., 2016; Morse et al., 2016). QIF enables linking the quality results (i.e., QIF results) back to the design (i.e., STEP) and manufacturing (i.e., MTConnect) domains.

Figure 5 Four standard data representations, ISO 10303, ISO 6983, MTConnect, and QIF were included in the reference implementation deployed at NIST

Notes: ISO 10303, or STEP, provides all relevant product design information, e.g., geometry; ISO 6983, or G-code, provides the process information as-planned, including feed rates and spindle speeds; MTConnect provides the actual path and speeds of the machine tool; and QIF provides inspection-related information, such as the inspection plan and results.

3.2 Fusing product lifecycle data

We perform data fusion by first presenting (human readable) and representing (machine readable) the appropriate data from design, planning, manufacturing, and inspection. Figure 5 provides an example of the machine-readable data collected for the part described in Section 4. It is important to note that the correct data items to include from each lifecycle stage again depends on the type of question or decision being addressed and may not include data from all lifecycle stages. For example, the use case demonstrated in Section 4 focuses on potential quality and production scheduling issues caused by a manufacturing process that does not perform as planned. The issues created in this use case influence all four stages, and potential solutions exist across the lifecycle based on the perspective and focus of the actors in each lifecycle stage:

- (*Design*) Can the part be redesigned to avoid the need for manufacturing processes that do not occur as planned?

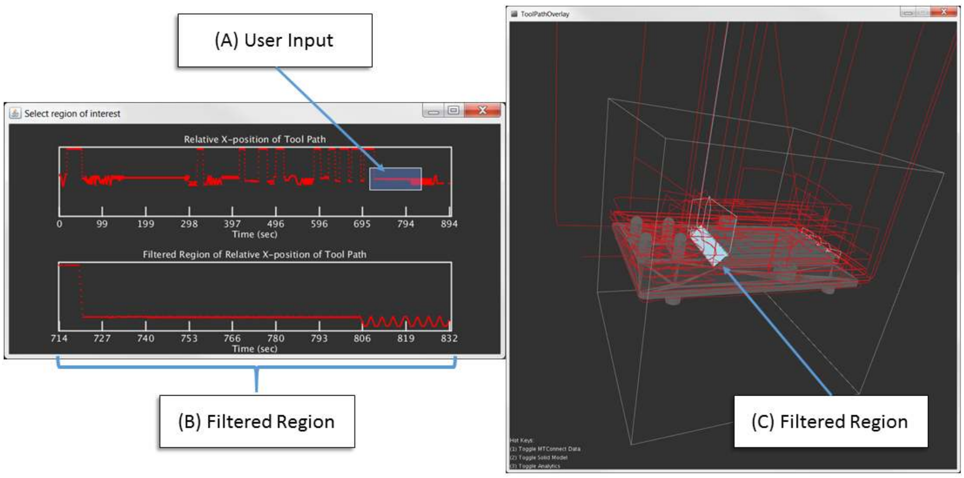
- (*Planning*) Can the toolpath be redesigned to minimise the impact of the process dynamics that cause process discrepancies?
- (*Manufacturing*) Can the operator be supported to make informed changes that compensate for any process discrepancies?
- (*Inspection*) Can the inspection plan be informed to focus on features impacted most by process discrepancies?

To address these questions, we need data from design, planning, and manufacturing, which we have available from the NIST SMS Test Bed (see Figure 4). Please note that we have purposefully excluded QIF data from inspection since the use case in Section 4 focuses on discrepancies in the manufacturing process, which are not caused by any decision in inspection but rather may impact decisions to be made during inspection. After collecting the appropriate data, we fuse each dataset by visually overlaying the three types of data. The visual overlaying process was performed manually through two steps:

1. colouring the as-executed toolpath based on the ratio of the programmed to actual process parameters
2. spatially matching the coloured, as-executed toolpath to the computer-aided design (CAD) geometry.

Areas with large discrepancies between the as-planned and as-executed states can then be mapped back to the portion of the toolpath and the feature of the part where they occur. A subsequent analysis of the underlying causes of these discrepancies can then be conducted as described in Section 4.

Figure 6 Screenshot of prototype built in Processing 2.0 (see online version for colours)



Notes: Here, we allow for direct manipulation of an STL representation of the test part. (A) Time-based plot of the x-coordinate during the build of the part. Here, the user can select a specific region of interest via brushing over the plot. (B) Based on the user selection, the region of interest is plotted to better display points of interest, or anomalies. (C) The 3D object viewer displays the filtered region in light blue onto the part. Here, we can see that the area of interest is on the slanted face of the part's fins.

4 Case study: demonstration of reference implementation

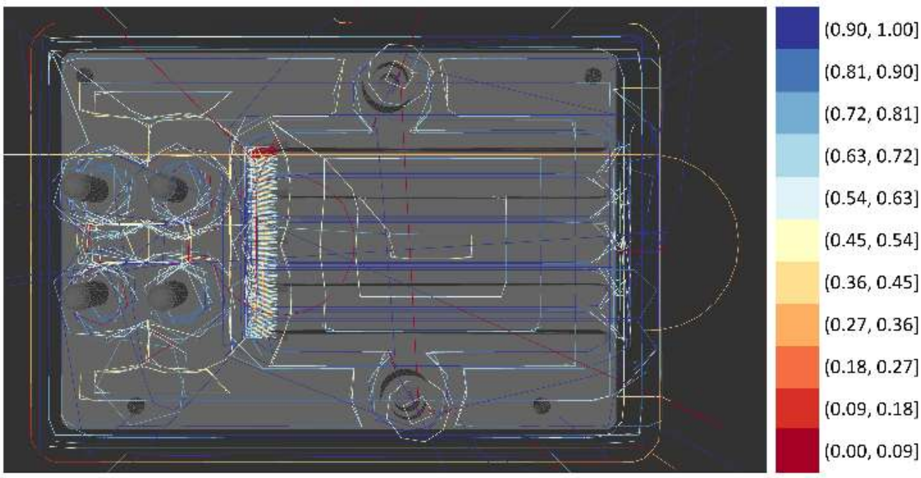
To demonstrate the opportunities provided by appropriately contextualising data through open standards-based approaches, we present a case study that uses our reference implementation to map design, planning, and execution data for an avionics heat sink test part as described in Section 3.1. This same part has been used in several other demonstrations (Brodsky et al., 216; Trainer et al., 2016). All of the data used in this demonstration is available and free for public use on the NISTSMSTest Bed (Hedberg and Helu, 2016). The setup information, initial cutting parameters, and cutting constraints for the test part were extracted from the technical data packages that are available on through the SMS Test Bed. The part was machined on a GF MIKRON HPM600U, which is a five-axis simultaneous milling centre. In the course of this exercise, we uncovered research opportunities and challenges associated with mapping between different perspectives across the lifecycle. Lessons learned from this implementation include a list of requirements for amending, appending, and improving any related standards as well as evidence for open research opportunities in the domain.

A prototype software was designed in Processing 2.0 (https://processing.org/), a Java-based interface development environment, to demonstrate the type of insight that can be drawn from relating different types of design and build information. The prototype interface (shown in Figure 6) includes two windows:

1 an object viewer with the tool path overlay as seen in Figure 7

2 a control window with a plot of the tool path on the x-axis against the duration of the build.

Figure 7 Visual overlay of MTConnect Data onto STL representation of an avionics heat sink part (see online version for colours)



Notes: The color of the each portion of the lines relates to the feed rate ratio, wherein the observed feed rate (MTConnect) is divided by the expected feed rate (NC code). Here, the deeper the blue the more the feed rate matched expectations.

In the control window, the user is able to filter a particular portion of the build based on the time and location of the tool path. This information includes a time-series plot of the x-coordinates from the MTConnect dataset. The user can query any portion of the build of the part by brushing over the desired portion of the time-series data. Once the desired area is selected, data relating to that query is emphasised in the object viewer window. Additionally, the user is afforded direct manipulation of the 3D part in the object viewer via OpenGL. The software also allows for dynamic toggling of the colour-coding capability and the tool path visualisation. It should be noted that the prototype, as-is, does not handle native STEP files. Here, we converted the reference STEP file to an STL using a commercial CAD package. We then scaled the tool path data, gathered via an MTConnect agent, to match features on the STL file.

Using the prototype, we generated Figure 7, illustrating one use case of this exercise. In this scenario, the design engineer would like to understand which features on the part took the most time to build to uncover opportunities for reducing operating costs. During process planning, a set of cutting parameters, including suggested feed rates, was specified. Using these values, the engineer can estimate the cost to build the part by calculating the amount of time required for each pass. However, in reality, practical issues such as the operator avoiding chatter affect the achieved feed rate when cutting specific features (Ridwan and Xu, 2013). Here, we apply a color scale representing the feed rate ratio to the tool path data. We define the feed rate ratio (f_r) as the observed feed rate (f_o) divided by the expected feed rate (f_e). The NC-code was compared with the MTConnect data and equation (1) was evaluated. The colourmap shown in Figure 7 was then encoded to each recorded point. In this case, we do not consider f_r values over 1 since these passes exceed the expectations of the build. Additionally, many of these cases relate to tool changes, which are not of interest from a design perspective.

$$f_r = \min\left(\frac{f_o}{f_e}, 1\right) \tag{1}$$

While a discrepancy between the observed and expected feed rate is to be expected because of the physical limitations of feed axes in a machine tool (e.g., non-infinite acceleration), there may still be room for improvement if such limitations can be considered during design and planning (see questions in Section 3.2). For example, Figures 6 and 7 show that the chamfer feature on the fins of the heat sink had a relatively high degree of discrepancy as suggested by f_r. Further investigation shows that the build time for this feature is eight times longer than the expected build if the machine operated exactly as commanded by the G code, which indicates that this feature presents an area of potential improvement. This analysis was conducted using the MTconnectR package (https://cran.r-project.org/web/packages/mtconnectR/index.html), an open source R package that includes functions:

1 to simulate data, including position data, feed rate, and velocities based on G code

2 to compare actual and simulated data through chart-based visualisations.

4.1 Exploring the impact of lifecycle viewpoints

The use case used to demonstrate our reference implementation focused on sharing information about discrepancies in the execution of a manufacturing process with primarily design and planning. It is for this reason that inspection data was not fused. As we discussed in Section 3, the types of data that should be collected and fused will depend on the perspectives and viewpoints of the relevant actors in the lifecycle and the decisions that they must make and questions that they may pose.

To further consider the impact of lifecycle viewpoints on the context that must be provided, we can consider the operate, orchestrate, and originate (O3) Project (http://www.uilabs.org/project/o3-operate-orchestrate-and-originate-14-06-05/) funded by the Digital Manufacturing and Design Innovation Institute (DMDII) and led by STEP Tools. The use case in the O3 Project is to determine the conformance of manufacturing processes remotely using inspection results and adjust non-conforming processes using applications. Given the goals of this use case, data is required from design, planning, execution, and inspection. In fact the solution demonstrated by the O3 project focuses on existing industry data standards including AP242 (as designed),Gcode and AP238 (as planned), MTConnect (as executed), and QIF (as measured), which matches the standards used in our reference implementation at NIST.

5 Discussion and conclusions

In Sections 3 and 4, we discussed bringing together data from across the product lifecycle to enable observing relationships and building knowledge for making decisions. The process of linking the different data and adding context was manual. Manually going through the linking process is not ideal. However, there is no clear way to automatically link data from across the product lifecycle without some level of human interpretation and intervention. This is largely due to features and the identification (ID) of those features not being maintained consistently from one data format to the next.

For example, a hole feature and associated characteristics may be defined in STEP. It is difficult to align the fabrication process information, represented in MTConnect, back to the STEP file because the feature ID and most feature information is lost in the process planning and numerical-control (NC) programming step. MTConnect is able to output data about what the machine tool is doing in a time-series, but information is missing to enable linking data quickly back to the original design data in STEP. Linking inspection data is somewhat easier because QIF and STEP can both represent the features in their respective data formats. However, the feature IDs may not be consistent and thus might require a reconciliation process between the two domains.

Enabling such linking between different stages in the product lifecycle would help enable a set of powerful scenarios for decision makers. For example, identifying relationships between machine parameters and part quality would inform intelligent tuning of machining instructions as also suggested by the DMDII O3 Project. Furthermore, such a scenario could lead to advanced automated reasoning during the design of the product. Given historical data of multiple builds and inspection outcomes, it is feasible to suggest that new computer-supported tools could more fully equip engineering designers during decision-making. As a result, we believe that emphasis should be placed on automatically deriving defect reports that house design, manufacturing, as well as inspection data to quicken the development of new enabling technologies for the digital thread.

Hedberg et al. (2016) and Miller et al. (2017) propose concepts that would enable automating the linking of data. Miller et al. (2017) propose defining a MIM for the product lifecycle to standardise the information that must flow between each domain of the lifecycle. Miller et al. (2017) are conducting a Delphi study to determine the information requirements. This study is identifying the information used within specific workflows, the capabilities of 3D-CAD models to carry this information, and the implications. The MIM would provide standardisation to help industry's transition to model-based design (MBD) by providing a general framework upon which to build.

Work presented by Miller et al. (2017) could be combined with that of Hedberg et al. (2016). Hedberg et al. (2016) propose defining a common element model (CEM), which would include and extend the MIM. Hedberg et al. (2016) adopt Semantic Web (Berners-Lee et al., 2001) and Linked Data (Berners-Lee, 2006) concepts to dynamically link different domain models to generate the CEM. The CEM would include both the minimum information that is required to move between domains and the domain-specific information. The combination of the MIM and CEM would provide a strategy and standard framework for mapping data and information between domains. This would greatly enhance the methods we describe in this paper.

The aim of this paper is to suggest directions to improve the contextualisation of manufacturing data for lifecycle decision-making. In light of this challenge, we presented a reference implementation through an interactive software prototype that demonstrated the importance of contextualising several sets of data across the lifecycle. This demonstration presented key open research opportunities that should be explored in more detail throughout the community.

Disclaimer

Acknowledgements

We wish to thank Mark Carlisle (NIST), John Michaloski (NIST), Dr. Vijay Srinivasan (NIST), Dr. Xenia Fiorentini (Engisis) and the journal peer-reviewers for their review and comments.

References

ASME Y14.5 (2009) *Dimensioning and Tolerancing*, American Society of Mechanical Engineers, New York, NY, USA.

Berners-Lee, T. (2006) *Linked Data* [online] http://www.w3.org/DesignIssues/LinkedData.html (accessed 31 March 2017).

Berners-Lee, T., Hendler, J. and Lassila, O. (2001) *The Semantic Web*, Scientific American, May [online] http://www.scientificamerican.com/article/the-semantic-web/ (accessed 31 March 2017).

Brodsky, A., Krishnamoorthy, M., Bernstein, W.Z. and Nachawati, M.O. (2016) 'A system and architecture for reusable abstractions of manufacturing processes', in *Proceedings of the 2016 IEEE International Conference on Big Data*.

Buxton, D., Farr, R. and MacCarthy, B. (2006) 'The aero-engine value chain under future business environments: using agent-based simulation to understand dynamic behaviour', in *Proceedings of the 8th International Conference on Modern Information Technology in the Innovation Processes of the Industrial Enterprises (MITIP)*.

Campos, J.G. and Hardwick, M. (2006) 'A traceability information model for CNC manufacturing', *Computer-Aided Design*, Vol. 38, No. 5, pp.540–551.

Cooper, R.G. (2001) *Winning at New Products: Accelerating the Process from Idea to Launch*, 3rd ed., Perseus Pub., Cambridge, Mass., ISBN: 0738204633.

Derhamy, H., Eliasson, J., Delsing, J. and Priller, P. (2015) 'A survey of commercial frameworks for the internet of things', in *Proceedings of the 2015 IEEE 20th Conference on Emerging Technologies & Factory Automation (ETFA)*, IEEE, pp.1–8.

Dimensional Metrology Standards Consortium (DMSC) (2014) *Part 1: Overview and Fundamental Principles in Quality Information Framework (QIF) – An Integrated Model for Manufacturing Quality Information* [online] http://qifstandards.org/ (accessed 31 March 2017).

Dinesh Kumar, U., Saranga, H., Ramírez Márquez, J.E. and Nowicki, D. (2007) 'Six Sigma project selection using data envelopment analysis', *The TQM Magazine*, Vol. 19, No. 5, pp.419–441, DOI: 10.1108/09544780710817856.

Feeney, A.B., Frechette, S.P. and Srinivasan, V. (2015) 'A portrait of an ISO STEP tolerancing standard as an enabler of smart manufacturing systems', *Journal of Computing and Information Science in Engineering*, Vol. 15, No. 2, pp.021001–021001, ISSN: 1530-9827, DOI: 10.1115/1.4029050.

Gallagher, M.P., O'Connor, A.C. and Phelps, T. (2002) *Economic Impact Assessment of the International Standard for the Exchange of Product Model Data (STEP) in Transportation Equipment Industries* [online] https://www.rti.org/sites/default/files/resources/STEP_Transport.pdf (accessed 3 February 2017).

Gardner, M. and Wiggs, G. (2013) 'Design for Six Sigma: the first 15 years', in *ASME Turbo Expo 2013: Turbine Technical Conference and Exposition*, American Society of Mechanical Engineers, p.V07AT28A006.

Hedberg Jr., T. and Helu, M. (2016) *NIST Smart Manufacturing Systems Test Bed* [online] http://smstestbed.nist.gov (accessed 15 December 2016).

Hedberg Jr., T., Feeney, A.B., Helu, M. and Camelio, J.A. (2016) 'Towards a lifecycle information framework and technology in manufacturing', *Journal of Computing and Information Science in Engineering*, DOI: 10.1115/1.4034132.

Hedberg Jr., T.D., Hartman, N.W., Rosche, P. and Fischer, K. (2017) 'Identified research directions for using manufacturing knowledge earlier in the product life cycle', *International Journal of Production Research*, Vol. 55, No. 3, pp.819–827, ISSN: 0020-7543, DOI: 10.1080/00207543.2016.1213453.

Heller, M. (2016) *V&V50 Verification and Validation of Computational Modeling for Advanced Manufacturing* [online] https://cstools.asme.org/csconnect/CommitteePages.cfm?Committee=101978604 (accessed 22 December 2016).

ISO 10303-1 (1994) *Industrial Automation Systems and Integration – Product Data Presentation and Exchange – Part 1: Overview and Fundamental Principles*, International Organization for Standardization, Geneva, Switzerland.

ISO 10303-238 (2007) *Industrial Automation Systems and Integration – Product Data Presentation and Exchange – Part 238: Application Protocol: Application Interpreted Model for Computerized Numerical Controllers*, International Organization for Standardization, Geneva, Switzerland.

ISO 10303-242 (2014) *Industrial Automation Systems and Integration – Product Data Presentation and Exchange – Part 242: Application Protocol: Managed Model Based 3D Engineering*, International Organization for Standardization, Geneva, Switzerland.

ISO 14638 (2015) *Geometrical Product Specifications (GPS) – Matrix Model*, International Organization for Standardization, Geneva, Switzerland.

ISO/IEC/IEEE 15288:2015 (2015) *Systems and Software Engineering – System Life Cycle Processes*, International Organization for Standardization, Geneva, Switzerland.

Johansson, C., Hicks, B., Larsson, A.C. and Bertoni, M. (2011) 'Knowledge maturity as a means to support decision making during product-service systems development projects in the aerospace sector', *Project Management Journal*, Vol. 42, No. 2, pp.32–50, ISSN: 87569728, DOI: 10.1002/pmj.20218.

Kelley, T. and Littman, J. (2001) *The Art of Innovation: Lessons in Creativity from IDEO, America's Leading Design Firm*, 1st ed., Currency/Doubleday, New York, ISBN: 0385499841.

Le Novère, N., Finney, A., Hucka, M., Bhalla, U.S., Campagne, F., Collado-Vides, J., Crampin, E.J., Halstead, M., Klipp, E., Mendes, P. et al. (2005) 'Minimum information requested in the annotation of biochemical models (MIRIAM)', *Nature Biotechnology*, Vol. 23, No. 12, pp.1509–1515.

Lee, J., Lapira, E., Bagheri, B. and Kao, H. (2013) 'Recent advances and trends in predictive manufacturing systems in big data environment', *Manufacturing Letters*, Vol. 1, No. 1, pp.38–41.

Liu, L. and Leitner, D. (2012) 'Simultaneous pursuit of innovation and efficiency in complex engineering projects: a study of the antecedents and impacts of ambidexterity in project teams', *Project Management Journal*, Vol. 43, No. 6, pp.97–110, ISSN: 1938-9507, DOI: 10.1002/pmj.21301.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C. and Byers, A.H. (2011) *Big Data: The Next Frontier for Innovation, Competition, and Productivity*, Technical Report, McKinsey Global Institute.

Miller, A.M., Hartman, N., Hedberg Jr., T., Feeney, A.B. and Zahner, J. (2017) 'Towards identifying the elements of a minimum information model for use in a model-based definition', in *2017 Manufacturing Science and Engineering Conference*, American Society of Mechanical Engineers, in press.

Morse, E., Heysiattalab, S., Feeney, A.B. and Hedberg Jr., T. (2016) 'Interoperability: linking design and tolerancing with metrology', *Procedia CIRP*, Vol. 43, pp.13–16, ISSN: 2212-8271, DOI: 10.1016/j.procir.2016.04.106.

Moss, L.T. and Atre, S. (2003) *Business Intelligence Roadmap: The Complete Project Lifecycle for Decision-Support Applications*, Addison-Wesley, Boston, MA, ISBN: 0201784203.

MTConnect Institute (2014) *Mtconnect Standard* [online] http://www.mtconnect.org/ (accessed 31 March 2017).

Munassar, N.M.A. and Govardhan, A. (2010) 'A comparison between five models of software engineering', *IJCSI International Journal of Computer Science Issues*, Vol. 7, No. 5, pp.94–101.

Pande, P.S., Neuman, R.P. and Cavanagh, R.R. (2014) *The Six Sigma Way: How to Maximize the Impact of Your Change and Improvement Efforts*, 2nd ed., McGraw-Hill Education, New York, ISBN: 9780071497329.

Parrino, R., Poteshman, A.M. and Weisbach, M.S. (2005) 'Measuring investment distortions when risk-averse managers decide whether to undertake risky projects', *Financial Management*, Vol. 34, No. 1, pp.21–60, ISSN: 1755-053X, DOI: 10.1111/j.1755-053X.2005.tb00091.x.

Pirolli, P. and Card, S. (1999) 'Information foraging', *Psychological Review*, Vol. 106, No. 4, p.643.

Richardson, L. and Ruby, S. (2008) *RESTful Web Services*, O'Reilly Media, Inc, Sebastopol, CA, USA.

Ridwan, F. and Xu, X. (2013) 'Advanced CNC system with in-process feed-rate optimisation', *Robotics and Computer-Integrated Manufacturing*, Vol. 29, No. 3, pp.12–20.

Ruemler, S.P., Zimmerman, K.E., Hartman, N.W., Hedberg Jr, T.D. and Barnard Feeney, A. (2017) 'Promoting model-based definition to establish a complete product definition', *Journal of Manufacturing Science and Engineering*, Vol. 139, No. 5, pp.051008.

Salado Diez, A. (2014) *Measuring and Influencing Problem Complexity and its Impact on System Affordability during Requirements Elicitation for Complex Engineered Systems*, PhD dissertation, Stevens Institute of Technology.

Schrage, M. (2000) *Serious Play: How the World's Best Companies Simulate to Innovate*, Harvard Business School Press, Boston, Mass., ISBN: 0875848141 (alk. paper).

Smith, B., Ashburner, M., Rosse, C., Bard, J., Bug, W., Ceusters, W., Goldberg, L.J., Eilbeck, K., Ireland, A., Mungall, C.J. et al. (2007) 'The OBO foundry: coordinated evolution of ontologies to support biomedical data integration', *Nature Biotechnology*, Vol. 25, No. 11, pp.1251–1255.

Smith, C. (2007) *Making Sense of Project Realities: Theory, Practice and the Pursuit of Performance*, Gower; Ashgate Publishing, Aldershot, England Burlington, VT, ISBN: 9780566087295.

Stacey, M. and Eckert, C. (2003) 'Against ambiguity', *Computer Supported Cooperative Work (CSCW)*, Vol. 12, No. 2, pp.153–183, ISSN: 1573-7551, DOI: 10.1023/a:1023924110279.

Thomke, S.H. (2001) 'Enlightened experimentation: the new imperative for innovation', *Harvard Business Review*, Vol. 79, No. 2, pp.66–75.

Trainer, A., Hedberg Jr., T., Feeney, A.B., Fischer, K. and Rosche, P. (2016) 'Gaps analysis of integrating product design, manufacturing, and quality data in the supply chain using model-based definition', in *2016 Manufacturing Science and Engineering Conference*, American Society of Mechanical Engineers, DOI: 10.1115/MSEC2016-8792.

Ullman, D.G. (2010) *The Mechanical Design Process*, 4th ed., McGraw-Hill Series in Mechanical Engineering, McGraw-Hill Higher Education, Boston.

Waurzyniak, P. (2013) 'Driving digital tools to the cloud', *Manufacturing Engineering*, Vol. 150, No. 4, pp.51–58.

Xu, X. and Newman, S.T. (2006) 'Making CNC machine tools more open, interoperable and intelligent: a review of the technologies', *Computers in Industry*, Vol. 57, No. 2, pp.141–152.