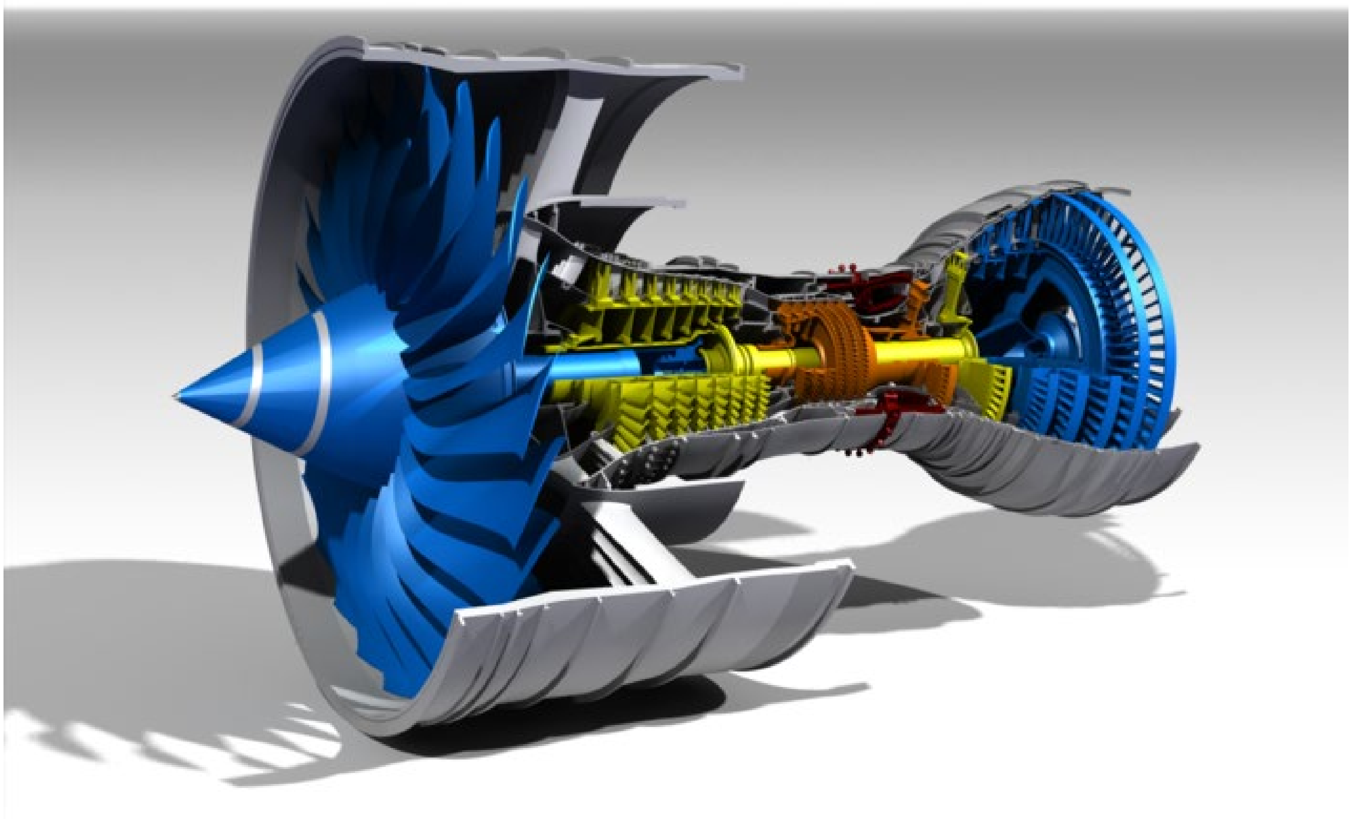
NIST Advanced Manufacturing Series 100-26

The Model Based Enterprise

A Literature Review of Costs and Benefits for Discrete Manufacturing



Douglas Thomas

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https://doi.org/10.6028/NIST.AMS.100-26

National Institute of Standards and Technology
U.S. Department of Commerce

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August 2019

U.S. Department of Commerce
Wilbur L. Ross, Jr., Secretary

National Institute of Standards and Technology
Walter Copan, NIST Director and Undersecretary of Commerce for Standards and Technology

Abstract

Currently, there is a limited understanding of the costs related to suboptimal design and production information in discrete manufacturing. There is incomplete information on how engineers and other staff use their time. Additionally, the rate and cause of defective or deficient products is not tracked at the industry level. The frequency and impact of low-quality design data on product research and development is not clear. Further, it isn't clear to what extent improved process modeling can improve efficiency. This report focuses on the costs and losses associated with inadequate design/modeling information and data in discrete manufacturing.[1] This includes:

- Product models (e.g., CAD/CAM)
- Simulation models of manufacturing processes
- Interoperability between software platforms

Design data has significant relevance to discrete medium-tech and high-tech manufacturing, which includes production of machinery, computers, electronics, and transportation equipment.

Currently available literature suggests that product and manufacturing information (PMI) embedded 3D models are not widely adopted for product designs, as only an estimated 26.8 % of survey respondents had 51 % or more of their designs released with PMI embedded 3D models. This research suggests that this type of modeling data can reduce redundant activities which include an estimated $8.40 billion spent on engineers answering questions and creating additional drawing documentation and $3.84 billion for machinists to do the same. Another study estimates the savings from managing digital data streams through models (Computer Aided Design or CAD models including material characteristics, simulation models of part creation and plant layout, and rapid automated costing functions) to be $8.9 billion and an additional $10.3 billion potential savings through seamless transmission of digital information (wireless transmission of data, seamless integration of sensors, and interoperability between CAD and computer aided manufacturing (CAM) platforms, and secure data transmission). Some of these items, however, include more than costs relevant to modeling/design. Costs associated with interoperability of varying data formats, a related issue, is estimated to be between $20.9 and $42.9 billion.

To collect data on costs/losses relevant to inadequate modeling and designs, an estimated minimum sample size of 31 would be needed. This is calculated with a 90 % confidence interval and a 20 % margin of error. A margin of error of 10 % would require a sample size of 122.

[1] For this report, discrete manufacturing includes codes 333-336 of the North American Industry Classification System

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Key words

Model based enterprise; economics; manufacturing.

1. Introduction

US manufacturing involves a large set of complex processes that stretch across extensive supply chains. It consists of thousands of establishments with millions of employees making trillions of dollars in goods. Frequently, engineers design products and then the designs are transferred to one or more groups responsible for production. The production group might be on- or offsite and could be within another company. Subcomponents are often then sent to yet other production groups. Moreover, the designs might change hands many times. The accuracy, completeness, and speed of design information transfer can become a critical element of efficient and high-quality production. Flaws in design information transfer can result in additional labor costs for design clarification, inferior products, or deficient products. The quality of design information also facilitates analysis of products, processes, and logistics. With high quality information, manufacturers can more readily make improvements in efficiency and product performance.

The National Institute of Standards and Technology's Model-Based Enterprise program is developing standards, test methods, and measurement science needs that enable manufacturers to integrate system, service, product, process, and logistics models across the manufacturing enterprise.[2] A Model-Based Enterprise (MBE) is an organization that applies modeling and simulation technologies to integrate and manage its technical and business processes related to production and product lifecycle support."[3]

Currently, there is a limited understanding of the costs related to suboptimal design/ model information and data. There is incomplete information on how engineers and other staff use their time. Additionally, the rate and cause of defective or deficient products is not tracked at the industry level. The frequency and impact of low-quality product design data on research and development is not clear. Further, it isn't clear to what extent improved process modeling can improve efficiency.

2. Scope and Approach

This report focuses on the costs and losses associated with inadequate design and modeling information/data in discrete manufacturing.[4] This includes:

- Product models (e.g., CAD/CAM)
- Simulation models of manufacturing processes
- Interoperability between software platforms

Design data has significant relevance to discrete medium-tech and high-tech manufacturing, which includes production of machinery, computers, electronics, and transportation equipment. It has more limited application to food, chemicals, and other non-durable goods such as paper, as these products have limited benefits from high quality two- and three-dimensional product designs. The logistics of product ordering (i.e., purchases) might be impacted by software interoperability and manufacturing

[2] National Institute of Standards and Technology. Model-Based Enterprise: Program Plan. https://www.nist.gov/sites/default/files/documents/2018/11/05/programsummary_mbe.pdf
[3] Frechette, Simon. "Model Based Enterprise for Manufacturing." 44th CIRP International Conference on Manufacturing Systems. Madison, WI. June 2011. https://www.nist.gov/publications/model-based-enterprise-manufacturing
[4] For this report, discrete manufacturing includes codes 333-336 of the North American Industry Classification System

processes might be impacted by process modeling, which might arguably be related to machinery manufacturing (i.e., design data for the machinery used in production). Modeling can impact both the product and the process, as there can be discrete simulation models of the manufacturing process and there can be process simulation of the product being produced.

Examining potential efficiency improvements often have either a solution-based focus or a problem/cost-based focus. The difference is somewhat subtle or blurred but it is perceptible and it impacts the application of the data along with the revealed insights. As illustrated in Figure 2.1, a solution-based approach in manufacturing examines the reduced cost that might result from a particular improvement, investment, or technology. For instance, examining the impact of adopting energy efficient lighting. An alternative to a solution-based approach is a problem/cost-based approach where costs are categorized by more natural classifications and avoids specifying a solution. For instance, examining the total expenditures on energy for lighting. There are many solutions to reducing lighting costs (e.g., energy efficient lighting, turning off some lights, or inserting skylights) and a solution-based approach could be used to examine each, but each of these solutions addresses a particular cost characterized in a problem-based approach. This report has a problem/cost-based focus where it aims to examine the costs that manufacturers face relevant to design and modeling. The benefit of such

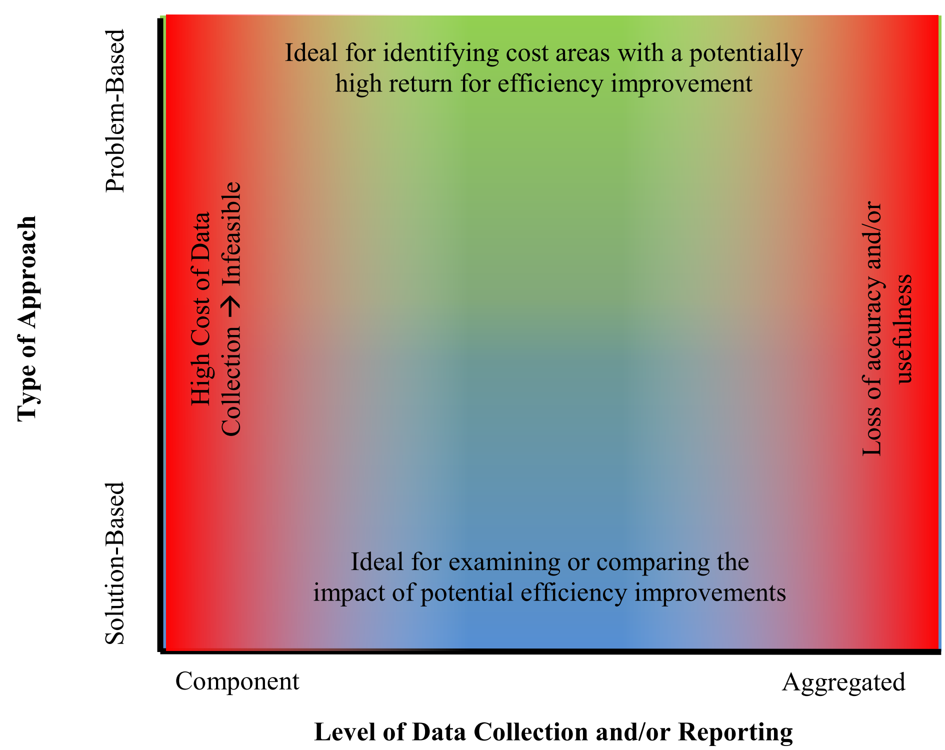

Figure 2.1: Categories of Cost Analysis

a focus is that it does not assume a solution; that is, it provides information that measures the magnitude of the problem to be solved (i.e., the costs associated with inadequate designs and/or modeling information). Thus, it presents a problem to be solved rather than a solution to be evaluated.

Another aspect of a cost analysis is the aggregation of costs. At least two challenges arise with high levels of aggregation. The first is the accuracy of the analysis. If data for an analysis is gathered at too aggregated of a level, there is the risk of a loss of accuracy, particularly in a solution-based approach, as this approach often cuts across natural cost categories tracked by a firm. To illustrate, consider a survey that asks someone to estimate the hours per year they spend driving their car compared to one that asks each component of their drive time (e.g., number of hours per day they spend driving to and from work). An aggregated question such as one on the total hours per year they spend driving is difficult to answer, as they must consider all at once the different places that they drive. Someone is much more likely to estimate with accuracy the amount of time they spend driving to work and other individual components of their total driving. The second challenge with high levels of aggregation is that it limits the insights of being able to identify solutions or efficiency improvements. The more aspects of the costs that are measured, the more possible solutions that may be identified and compared. Unfortunately, the more components there are, the higher the cost in data collection and analysis, which could make a study infeasible. This report will aim to measure detailed components of costs associated with inadequate designs and modeling.

3. Cost Literature

The relevant cost literature, typically, does not focus specifically on the costs, benefits, and losses associated with having or not having a model-based enterprise. Rather, it tends to focus on related subcategories and/or case studies. Section 3.1 presents relevant case studies while Section 3.2 presents industry level analyses.

3.1. Case Studies and other Narratives

Boeing: A recent case study that is relevant to the quality of design data is found in the 787 Dreamliner where Boeing took a new approach for production. While Boeing's previous production methods custom built each airplane at a single location, Airbus had embraced modular design where subassemblies were manufactured offsite and then shipped to one location for assembly. Boeing had decided to adopt a similar method of production for the 787 Dreamliner where subassemblies would be sourced from other companies. Sections of the plane would be built all over the world with the forward fuselage built in Japan, wingtips from Korea, center fuselage from Italy, and other parts from Australia, England, Sweden, and the United States.

This method would require rapid, efficient, and accurate transfer of design data for any changes in design. It was believed that this approach would reduce development costs from $10 billion to $6 billion and reduce development time from 6 to 4 years. Ultimately, the project was billions of dollars over budget and 3 years behind schedule. The first airplane was delivered 40 months behind schedule.[5]

It has been suggested that the success of modular design relies on the design being set by the Original Equipment Manufacturer (OEM) early on and on subassembly manufacturers having the flexibility to make changes on their own initiative, as long as it does not reduce performance.[6] Boeing, unexpectedly, had to send hundreds of engineers to its Tier-1, Tier-2, and Tier-3 suppliers to support on-site quality, supplier-management, and technical support.[7] The company had to redesign the entire aircraft sub-assembly process. One of the problems was that some parts did not fit together resulting in extensive rework. Boeing had to purchase some of its suppliers and bring some work back in-house. One of the problems was traced back to the failure to clearly communicate requirements and data to suppliers. [8]

Supply-management executive Ben Funston at Boeing said that they, "needed a tool to give us situational awareness into the production system, the ability to have early issue detection and real-time problem resolution." [9] This type of solution requires a complete understanding of the production system. Boeing created a Production Integration Center (PIC) to achieve this goal. This center monitored conditions around the world and served

[5] McDonald, Rory and Suresh Kotha. "Boeing 787: Manufacturing a Dream." Harvard Business School. 9-615-048. May 29, 2015.
[6] Sarkar, Suman. The Supply Chain Revolution: Innovative Sourcing and Logistics for a Fiercely Competitive World. American Management Association. New York, NY. 2017. 39-43.
[7] Denning, Steve. "What Went Wrong at Boeing?" Forbes. January 21, 2013. https://www.forbes.com/sites/stevedenning/2013/01/21/what-went-wrong-at-boeing/#47ee359d7b1b
[8] Sarkar, The Supply Chain Revolution. 42.
[9] McDonald, "Boeing 787: Manufacturing a Dream."

as a call center to resolve problems as they arise at supplier locations. Information from Boeing's partners were used to develop routines and graphic-display techniques to monitor manufacturing processes around the globe. Addressing both design and production issues, PIC improved communication and collaboration, making it pivotal in stabilizing Boeing's 787 supply chain.

IMTI: The Integrated Manufacturing Technology Initiative is a member-based organization that supports technology advancements in US manufacturing. Discussions within this organization indicated cost reductions from model-based tools have exceeded 50 %. In DoD ground vehicles, production development was reduced from 2 years to 90 or 120 days. In construction equipment, a manufacturer indicated that product development time was reduced from 27 months to 9 months. Boeing reported a 91 % time savings and 71 % labor cost savings due to model-based tools. BAE systems reported time savings of seven fold. Proctor and Gamble documented savings exceeding $1 billion annually with 30 % to 40 % improvement in equipment reliability and 60 % to 70 % faster startup for new equipment and product initiatives.[10] Major defense contractors from the US MBE team estimated that the implementation of the Model-Based Enterprise would cut costs by 50 % and reduce time to market by 45 %; however, this estimate seems to be a best guess rather than the result of data analysis.[11]

LMI: A presentation by LMI regarding work sponsored by the Defense Logistics Agency (DLA) indicated that DLA could avoid $939 million per year for consumable spare parts with improved data. Additionally, it was estimated that data challenges result in the cost of spare parts being 2.1 times greater.[12, 13]

Aberdeen Group: Investigations from the Aberdeen Group reported that 3D models reduce development cycles by 30 % to 50 % and reduces non-conformances by 30 % to 40 %.

CIMdata: In its work with DELMIA Solutions, CIMdata indicated that there was

- 10 % reduction in overall product design time
- 30 % savings in tool design
- 65 % reduction in the number of design changes
- 15 % savings due to improved quality from validation of processes prior to production
- 13 % savings in overall production cost
- 15 % increased production throughput
- 30 % reduction in overall time to market

[10] Integrated Manufacturing Technology Initiative, Inc. "Intelligent, Integrated Manufacturing Systems." October 2009. Available upon request from http://www.imti2020.org/.
[11] IMTI, Inc. "Incentives White Papers for Advanced Manufacturing Technology." Department of Defense. Section 1-4. https://www.acq.osd.mil/mibp/natibo/docs/00-Consolidated%20Overview%20&%20DoD%20Incentives%20White%20Papers%2015%20April%2009.pdf
[12] Kaplan, Bruce. "Why Digital Tech Data?" DMSMS 2010 Plenary Panel. http://meetingdata.utcdayton.com/agenda/dmsms/2010/proceedings/presentations/P4039.pdf
[13] Leonard, Scott and Mel Hafer. Advanced Manufacturing Enterprise: Strategic Baseline. 2011. https://www.dodmantech.com/JDMTP/Files/AME_Strategic_Baseline_03_Nov_11.pdf

CIMdata also indicated that it was reasonable to expect returns on investment ranging from 5/1 to 10/1 when digital manufacturing software is implemented with digital mockup, process re-engineering, and as a component of integrated product life cycle solution.[14]

3.2. Industry Wide Studies

Case studies, anecdotal evidence, and other individual experiences are useful for understanding some aspects and impacts of advancing the model-based enterprise. However, it would be difficult to generalize these non-scientific observations to all of manufacturing or to an industry within manufacturing. To understand the total potential of advancing the model-based enterprise, studies at the industry level is discussed below.

Lifecycle Insights: Currently, 3D models are not widely adopted for product designs according to research by Lifecycle Insights. As seen Table 3.1, an estimated 26.8 % of survey respondents had 51 % or more of their designs released with PMI-embedded 3D

[14] CIMdata. "The Benefits of Digital Manufacturing." 2003. http://www.cimdata.com/publications/reports_complimentary/white_papers.html

Table 3-1: 3D Model Adoption and Use, Percent of Respondents (i.e., organizations)

No 3D Models

Heavy 3D Model User

What percent of your designs have been released with 2D drawings	What percent of your designs have been released with PMI-embedded 3D models: None (0%)	Little (1%-25%)	Some (26%-50%)	Majority (51%-75)	Most (76%-99%)	All (100%)	TOTAL
None (0%)	0.4	0.4	-	-	1.3	0.4	2.5
Little (1%-25%)	2.5	1.7	0.8	1.3	2.5	1.3	10.1
Some (26%-50%)	1.3	2.9	1.3	2.1	-	-	7.6
Majority (51%-75)	2.5	4.2	3.8	0.8	-	-	11.3
Most (76%-99%)	11.8	9.2	2.9	2.5	2.9	0.8	30.1
All (100%)	24.4	5.5	0.8	2.5	2.1	2.9	38.2
TOTAL	42.9	23.9	9.6	9.2	8.8	5.4	99.8
TOTAL (Excl. Grey)*	41.5	21.6	10.1	10.5	10.1	6.2	100.0

* This percentage is recalculated excluding those areas greyed out. The greyed areas are excluded as they represent designs that are neither 2D or 3D.
Note: Areas are greyed out due to designs that have neither 2D or 3D drawings. That is, the sum of 2D drawings and 3D drawings do not approximate 100 % of designs.
Source: Lifecycle Insights. Quantifying the Value of Model Based Definitions: Saving Time, Avoiding Disruptions, Eliminating Scrap. https://www.lifecycleinsights.com/wp-content/uploads/2018/04/LCI-MBD.pdf

models.[15] It is important to note that the model-based enterprise is more than 3D product models; however, this low adoption rate indicates that, potentially, there is an opportunity for improvement in utilizing models.

The 2014 State of Model Based Enterprise Report from Lifecycle Insights provides some insight on the costs related to the model-based enterprise. On average, engineers spend 21.3 hours per week creating drawings with an additional 6.4 hours answering questions and clarifying drawings and an added 5.5 hours generating additional drawing documentation. As seen in Table 3.2, the hours spent answering questions and making clarifications amount to an estimated $8.40 billion annually.[16] For machinists, it amounts to $3.84 billion annually. As seen in Figure 3.1, organizations that utilize 3D annotated models spend 6.6 fewer hours per week on engineering, have 2.5 fewer emergency issues

[15] This estimate excludes the numbers greyed out in Table 3.1
[16] The potential loss was calculated as the sum of the hours per week multiplied by the hourly wage. The product was multiplied by the total US employment and by the total weeks per year (52.1429).

(e.g., change orders and reprioritized resources), and have 4.9 fewer assessments per month on why parts do not fit together.[17]

Table 3-2: Labor Hours Spent Making Clarifications and Answering Questions

Occupation	Activity	Hours per Week	Mean Hourly Wage	Total US Employment	Potential Loss ($Billion)
Engineers	Answering questions or clarifying drawings	6.4	$44.62*	303 440*	8.40
	Creating additional drawing documentation	5.5			
Machinists	Answering questions or clarifying documentation	4.7	$21.75	384 350	3.84
	Generating additional documentation	4.1			

* Mechanical engineers

Sources: Lifecycle Insights. "Average Time Spent Authoring, Clarifying and Amending Documentation." The 2014 State of Model Based Enterprise Report. https://www.lifecycleinsights.com/finding/average-time-spent-authoring-clarifying-and-amending-documentation/
Bureau of Labor Statistics. "Occupational Employment Statistics." https://www.bls.gov/oes/current/oes_nat.htm

[17] Lifecycle Insights. "Quantifying the Value of Model Based Definitions: Saving Time, Avoiding Disruptions, Eliminating Scrap." Presentation. https://www.lifecycleinsights.com/wp-content/uploads/2018/04/LCI-MBD.pdf

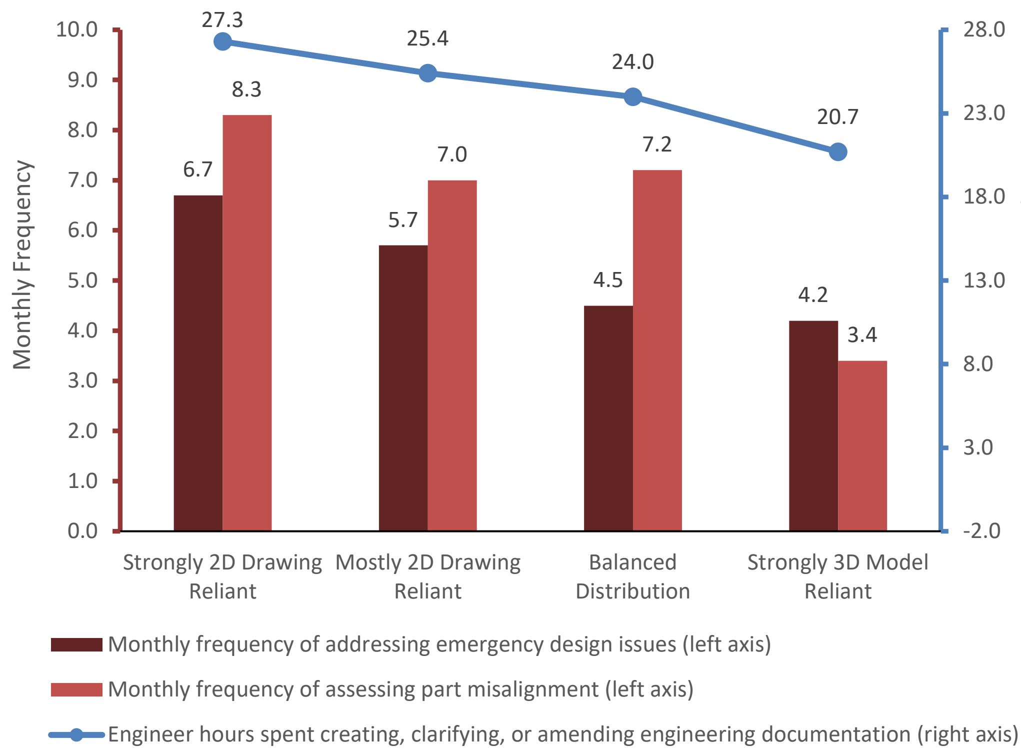

Figure 3.1: Frequency of Design Issues by 2D/3D Drawing Reliance

Source: Lifecycle Insights. "Quantifying the Value of Model Based Definitions: Saving Time, Avoiding Disruptions, Eliminating Scrap." Presentation. https://www.lifecycleinsights.com/wp-content/uploads/2018/04/LCI-MBD.pdf

Utilizing the data on engineering hours from Figure 3.1 combined with the data from Table 3.1, an estimate of the cost of engineering labor due to inefficiencies of relying on 2D models can be made:

$$C_E = \sum_{n=1}^{4} (H_n - H_4) * P_n * WAGE_E * EMPL_E * 54.1429$$

Where

C_E = Potential yearly cost of E, where E is the engineering labor due to inefficiencies in relying on 2D models

H_n = Engineering hours per week spent on creating, clarifying, or amending engineering documentation for groupings n, where n is groupings 1 through 4 from Appendix A (Group 1 – strongly 2D drawing reliant, Group 2 – mostly 2D drawing reliant, Group 3 – balanced distribution, and Group 4 – strongly 3D model reliant)

P_n = The percent of respondents by grouping n, where n is groupings 1 through 4 from Appendix A

$WAGE_E$ = The mean hourly wage for E, where E is engineers ($44.62)

$EMPL_E$ = Total occupational employment of E, where E is mechanical engineers

(303 440)

Note that 54.1429 is the number of weeks in a year. Using the equation above, the estimated potential cost of engineering labor due to inefficiencies in relying on 2D models is $3.6 billion. Note that this does not include other costs such as machinist labor and design problems.

To estimate the potential cost of machinist labor due to inefficiencies from relying on 2D models, one could assume the ratio of reduced hours to hours spent making clarifications and answering questions are the same for both engineering and machinists. The calculation for reduced hours would then be:

$$C_M = \sum_{n=1}^{4} \frac{(H_n - H_4)}{ENG} * MACH * P_n * WAGE_M * EMPL_m * 54.1429$$

Where

ENG = Total weekly engineering hours (6.4 + 5.5 = 11.9) spent making clarifications and answering questions from Table 3.2.

MACH = Total weekly machinist hours (4.7 + 4.1 = 8.8) spent making clarifications and answering questions from Table 3.2.

$WAGE_M$ = The mean hourly wage for M, where M is machinists ($21.75)

$EMPL_M$ = Total occupational employment of M, where M is machinists (384 350)

The total using this equation is $1.6 billion. The total of engineering costs and machinist costs for relying on 2D models is estimated as the sum of the $3.6 billion and $1.6 billion or $5.2 billion. This is an estimate of the subcomponent of labor cost spent making clarifications and answering questions (see Table 3-2) that might be reduced by using 3D models.

NIST Report on Smart Manufacturing: NIST research has estimated that if smart manufacturing technology infrastructure were implemented, it might save $57.4 billion.[18] Approximately $8.9 billion of this is due to managing digital data streams through models (CAD models including material characteristics, simulation models of part creation and plant layout, and rapid automated costing functions) and $10.3 billion is through seamless transmission of digital information (wireless transmission of data, seamless integration of sensors, interoperability between CAD/CAM platforms, secure data transmission, advanced data analysis/interpretation, predictive maintenance, and cloud computing). This estimate is made by interviewing 81 individuals in the manufacturing industry about the level of impact that adopting smart manufacturing technologies might have in costs. This was combined with asking about the importance of different factors within smart manufacturing, including "managing digital data streams through models."[19]

[18] Gallaher, Michael, Zachary Oliver, Kirsten Rieth, and Alan O'Connor. "Economic Analysis of Technology Infrastructure Needs for Advanced Manufacturing: Smart Manufacturing." NIST GCR 16-007. https://doi.org/10.6028/NIST.GCR.16-007

[19] Gallaher, "Economic Analysis of Technology Infrastructure"

NIST Report on Supply Chain Integration: Variations in data formats often result in the re-entry of data, creating an inefficient use of labor. Using interviews and a large-scale survey, an estimate of the cost due to these inefficiencies was estimated to be the equivalent of 1.25 % of automobile shipments and 1.22 % of electronic shipments, as shown in Table 3.3. Applying these percentages to the 2016 estimates for discrete manufacturing shows a cost of between $20.9 billion and $42.9 billion, as shown in Table 3-4.

Table 3-3: Cost Avoidance Estimates, 2004

Industry	Cost Avoidance	Metric
Automobile (inadequate interoperability) [1,2]	0.364%	of revenues
Automobile (inadequate infrastructure for supply chain integration) [1,3]	1.250%	of shipments
Electronics [1,3]	1.220%	of shipments

Sources: [1] Leonard, Scott and Mel Hafer. Advanced Manufacturing Enterprise: Strategic Baseline. https://www.dodmantech.com/JDMTP/Files/AME_Strategic_Baseline_03_Nov_11.pdf
[2] "Interoperability Cost Analysis of the U.S. Automotive Supply Chain," prepared for NIST by Research Triangle Institute, 1999. Pgs 5-2, 5-3. Download at www.rti.org/pubs/US_automotive.pdf
[3] White, William, Alan O'Connor, and Brent Rowe. "Economic Impact of Inadequate Infrastructure for Supply Chain Integration." RTI International. Planning Report 04-2. 2004. https://www.nist.gov/sites/default/files/documents/director/planning/report04-2.pdf

Table 3-4: Cost Avoidance Estimates, 2016

NAICS Code	NAICS Description	Shipments ($billions)	Cost Avoidance (low estimate)	Cost Avoidance (high estimate)
333	Machinery manufacturing	348.4	4.3	8.7
334	Computer and electronic product manufacturing	293.6	3.6	7.3
335	Electrical equipment, appliance, and components	124.2	1.5	3.1
336	Transportation equipment manufacturing	949.3	11.6	23.7
	Total	1715.5	20.9	42.9

Data Sources: Leonard, Scott and Mel Hafer. Advanced Manufacturing Enterprise: Strategic Baseline. https://www.dodmantech.com/JDMTP/Files/AME_Strategic_Baseline_03_Nov_11.pdf
Census Bureau. Annual Survey of Manufactures. https://www.census.gov/programs-surveys/asm.html

4. Cost Data

Industry-level manufacturing cost data largely consists of data categorized by industry NAICS code and occupation category. A discussion on industry-level manufacturing cost data is presented in NIST AMS 100-18.[20] The following draws a great deal from that report.

4.1. Relevant Data

There are a number of sources for aggregated data on manufacturing relevant to design/modeling or a lack thereof. These sources include the following:

- Annual Survey of Manufactures (Census Bureau 2018)
- Economic Census (Census Bureau 2018)
- Occupational Employment Statistics (Bureau of Labor Statistics 2018)
- Economic Input-Output Data (Bureau of Economic Analysis 2018)

These datasets are discussed in more detail below.

4.1.1. Annual Survey of Manufactures and Economic Census

The Annual Survey of Manufactures (ASM) is conducted every year except for years ending in 2 or 7 when the Economic Census is conducted. The ASM provides statistics on employment, payroll, supplemental labor costs, cost of materials consumed, operating expenses, value of shipments, value added, fuels and energy used, and inventories. It uses a sample survey of approximately 50 000 establishments with new samples selected at 5-year intervals. The ASM data allows the examination of multiple factors (value added, payroll, energy use, and more) of manufacturing at a detailed subsector level. The Economic Census, used for years ending in 2 or 7, is a survey of all employer establishments in the U.S. that has been taken as an integrated program at 5-year intervals since 1967. Both the ASM and the Economic Census use the North American Industry Classification System (NAICS); however, prior to NAICS the Standard Industrial Classification (SIC) system was used.[21,22] NAICS and SIC are classifications of industries, which are based primarily on the product produced (e.g., automobiles, steel, or toys). The categories include both intermediate and finished goods.

Together, the Annual Survey of Manufactures and the Economic Census provide annual data on manufacturing, including value added and capital. Value added is equal to the value of shipments less the cost of materials, supplies, containers, fuel, purchased electricity, and contract work. It is adjusted by the addition of value added by merchandising operations plus the net change in finished goods and work-in-process goods. Value added avoids the duplication caused from the use of products of some

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[20] Thomas, Douglas S. "The Costs and Benefits of Advanced Maintenance in Manufacturing." NIST AMS 100-18. April 2018. https://nvlpubs.nist.gov/nistpubs/ams/NIST.AMS.100-18.pdf
[21] Census Bureau. "Annual Survey of Manufactures." <https://www.census.gov/programs-surveys/asm.html />
[22] Census Bureau. "Economic Census." <https://www.census.gov/EconomicCensus>

establishments as materials. It is important to note that the Bureau of Economic Analysis (BEA), which is a prominent source of data on value added, and the ASM calculate value added differently. The BEA calculates value added as "gross output (sales or receipts and other operating income, plus inventory change) less intermediate inputs (consumption of goods and services purchased from other industries or imported)."[23] Moreover, the difference is that ASM's estimate of value added for manufacturing includes the value of purchases from other industries such as mining and construction while BEA's does not include it.

4.1.2. County Business Patterns

The County Business Patterns series extracts data from the Business Register, a database of companies maintained by the US Census Bureau. The annual Company Organization Survey is used to provide establishment data for multi-establishment companies while several sources such as the Economic Census, Annual Survey of Manufactures, and Current Business Survey are used to assemble data on single-establishment companies. The County Business Pattern data is assembled annually. This data provides payroll and the number of establishments by employee by industry (see Figure 4.1). The industries of primary concern for this paper include the following NAICS codes, as defined by the US Census Bureau[24]:

- NAICS 333: Machinery Manufacturing – "Industries in the machinery manufacturing subsector create end products that apply mechanical force, for example, the application of gears and levers, to perform work."
- NAICS 334: Computer and Electronic Product Manufacturing – "Industries in the computer and electronic product manufacturing subsector group establishments that manufacture computers, computer peripherals, communications equipment, and similar electronic products, and establishments that manufacture components for such products."
- NAICS 335: Electrical Equipment, Appliance, and Component Manufacturing – "Industries in the electrical equipment, appliance, and component manufacturing subsector manufacture products that generate, distribute and use electrical power. Electric lighting equipment manufacturing establishments produce electric lamp bulbs, lighting fixtures, and parts. Household appliance manufacturing establishments make both small and major electrical appliances and parts. Electrical equipment manufacturing establishments make goods, such as electric motors, generators, transformers, and switchgear apparatus. Other electrical equipment and component manufacturing establishments make devices for storing electrical power (e.g., batteries), for transmitting electricity (e.g., insulated wire, and wiring devices (e.g., electrical outlets, fuse boxes, and light switches)."
- NAICS 336: Transportation Equipment Manufacturing – "Industries in the transportation equipment manufacturing subsector produce equipment for transporting people and goods. Transportation equipment is a type of machinery.

[23] Horowitz, Karen J. and Mark A. Planting "Concepts and Methods of the U.S. Input-Output Accounts." (2009): Glossary-32. http://www.bea.gov/papers/pdf/IOmanual_092906.pdf
[24] Census Bureau. "North American Industry Classification System." https://www.census.gov/eos/www/naics

An entire subsector is devoted to this activity because of the significance of its economic size in all three North American countries."

According to the most recently released data, which is for 2016, there are 52 927 establishments in NAICS codes 333-336.

4.1.3. Occupational Employment Statistics

The Occupational Employment Statistics program at the Bureau of Labor Statistics provides data on employment and wages for over 800 occupations in 415 industries categorized by the Standard Occupation Classification SOC) system and by NAICS code. It surveys between 180 000 to 200 000 establishments every six months with establishments being surveyed no more than once every 3 years. Data is available on the Bureau of Labor Statistics website back to 1988; however, more comprehensive data collection began in 1996.[25]

4.1.4. Economic Input-Output Data

Annual input-output data is available from the BEA for the years 1998 through 2016. Prior to 1998, the data is available for every fifth year starting in 1967. There is also data available for the years 1947, 1958, and 1963. More detailed data is available for years ending in two or seven. The input-output accounts provide data to analyze inter-industry relationships. BEA input-output data is provided in the form of "make" and "use" tables. Make tables show the production of commodities (products) by industry. Use tables show the components required for producing the output of each industry.

There are two types of make and use tables: "standard" and "supplementary." Standard tables closely follow NAICS and are consistent with other economic accounts and industry statistics, which classify data based on establishment. Note that an "establishment" is a single physical location where business is conducted. This should not be confused with an "enterprise" such as a company, corporation, or institution. Establishments are classified into industries based on the primary activity within the NAICS code definitions. Establishments often have multiple activities. For example, a hotel with a restaurant has income from lodging (a primary activity) and from food sales (a secondary activity). An establishment is classified based on its primary activity. Data for an industry reflects all the products made by the establishments within that industry; therefore, secondary products are included. Supplementary make-use tables reassign secondary products to the industry in which they are primary products.[26,27] The make-use tables are used for input-output analysis as developed by Leontief.[28,29]

[25] Bureau of Labor Statistics. "Occupational Employment Statistics: Overview." https://www.bls.gov/oes/oes_emp.htm
[26] Over the years BEA has made improvements to its methods. This includes redefining secondary products. The data discussed in this section utilizes the data BEA refers to as "after redefinitions."
[27] Horowitz, "Concepts and Methods," 4.1-4.10.
[28] Horowitz, "Concepts and Methods," 1.5.
[29] Miller, Ronald E. and Peter D. Blair. Input-Output Analysis: Foundations and Extensions. (New York, NY: Cambridge University Press, 2009): 16.

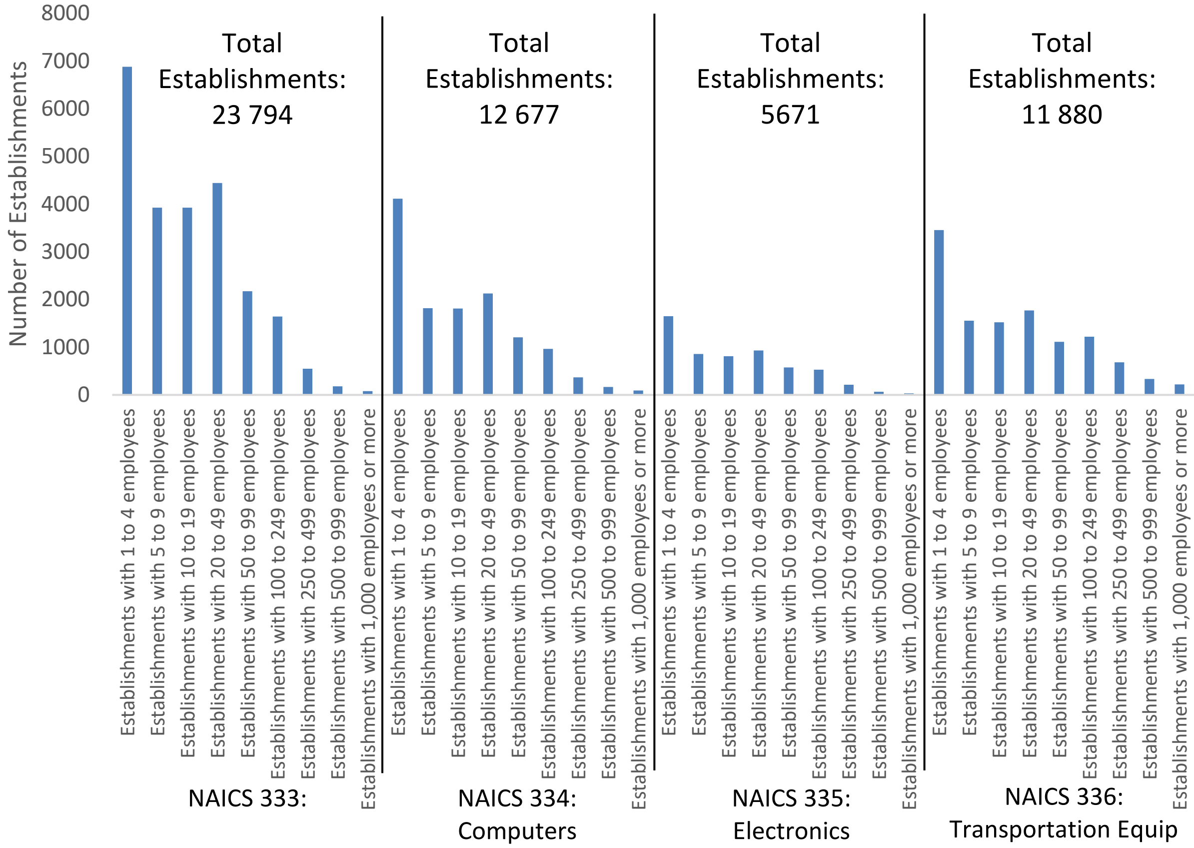

Figure 4.1: Number of Establishments by Employment, 2015

Source: Census Bureau. "Economic Census." 2018. <https://www.census.gov/EconomicCensus>

5. Cost Identification

One of the challenges of measuring the manufacturing costs impacted by a model-based enterprise is the classification of costs. Manufacturers each select their own cost categories that they recognize and track. To make industry level estimates, individually collected data will be combined with industry level data, which uses standardized classifications (e.g., NAICS). Further, manufacturers can be resistant to sharing some types of information. The result is that data collection needs to fit the following criteria (see Figure 4.1): the data is applicable to model based engineering, the data is feasible to collect, the data can be applied to standardized industry categories, and the data categories are recognizable to manufacturers.

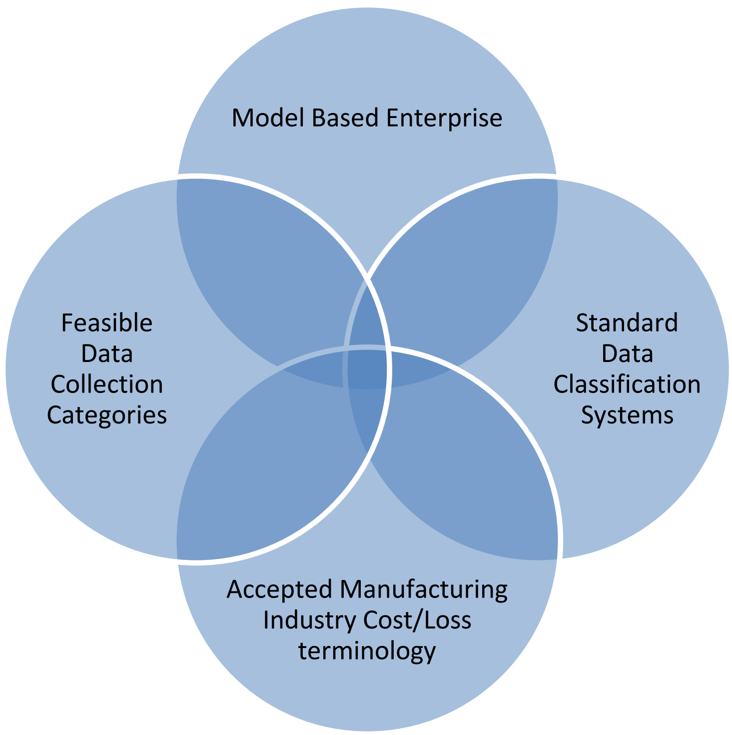

Figure 5.1: Requirements for Identifying Manufacturing Costs Associated with Model Based Engineering

Design data and modeling affect a great deal of manufacturing costs, as they can affect many aspects of production. Identifying the manufacturing costs that can be impacted becomes difficult, as it is not useful to simply measure the total cost of production. For this report, costs were separated into product-oriented costs and process-oriented costs. Product-oriented costs are those costs that relate to design data and the modeling of the product. Relevant cost categories are presented in Figure 5.2 and include modeling/design costs, data transfer costs, and redesign/rework of products due to design flaws or data transfer problems. Process-oriented costs are those impacted by the design of the production process (e.g., factory floor design). Relevant cost categories are presented in Figure 5.3 and include costs of increased/decreased work-in-process time, suboptimal process design, and supply chain design costs.

Some of these costs have data availability while others do not. In both Figure 5.2 and Figure 5.3 the costs are color coded according to data availability with green indicating that there is data available, yellow meaning there is research on or some data available on the cost category, and red indicating that there is limited or no data on the cost category.

From Figure 5.2, "1 Modeling/Design" has data available from the Bureau of Labor Statistics' Occupational Employment Statistics program. This data includes wages and employment. The data can be combined with the Current Employment Statistics' estimates for the average weekly hours worked to estimate the total cost of engineering labor. Cost "2 Design/Production Information Transfer to Production Facility or Supplier" does not have data collected regularly; however, the previously mentioned study by Gallaher et al. titled, "Economic Analysis of Technology Infrastructure Needs for Advanced Manufacturing: Smart Manufacturing" does estimate the impact of "seamless transmission of digital information." This study would also be applicable to the cost stage "3 Production/Prototyping."

Recall that a solution-based focus in manufacturing examines the reduced cost that might result from a particular improvement while a problem-based focus examines the costs that are incurred without specifying a solution. The study from Gallaher et al. examines multiple issues in manufacturing and might be considered a cross between a solution-based study and a problem-based study. For instance, it examines the cost savings from "managing digital data streams through models," which would be more of a solution-based focus, as it poses a specific solution: models (i.e., CAD models with material characteristics, simulation models of part creation, and automated costing functions). On the other hand, it seeks to also measure the savings from the seamless transmission of digital information, which is more of a problem-based focus, as it states a problem (i.e., transmission of digital information). Both categories, however, lump a number of problem-based cost categories together. For instance, it lumps process design costs with product design costs. The study by Gallaher et al. does not explicitly discuss redesign or rework; therefore, it is not entirely clear that respondents incorporated these costs/losses into their estimates, which is why they are shown in red and yellow in Figure 5.2. The literature revealed very little in regard to the impact of improved modeling on end use satisfaction, including lost sales, timeliness of product delivery, and the function of the products.

The "1 Work-in-Process" stage in the process-oriented costs (see Figure 5.3) has some data availability for flow time using the Annual Survey of Manufactures; however, there is only limited data on physical capital. There is no data tracking of down time and its associated costs; however, the estimates from Gallaher et al. include these costs as part of their examination on "managing digital data streams through models." Theoretically, this study could also include "2 Process Redesign due to Product Flaws"

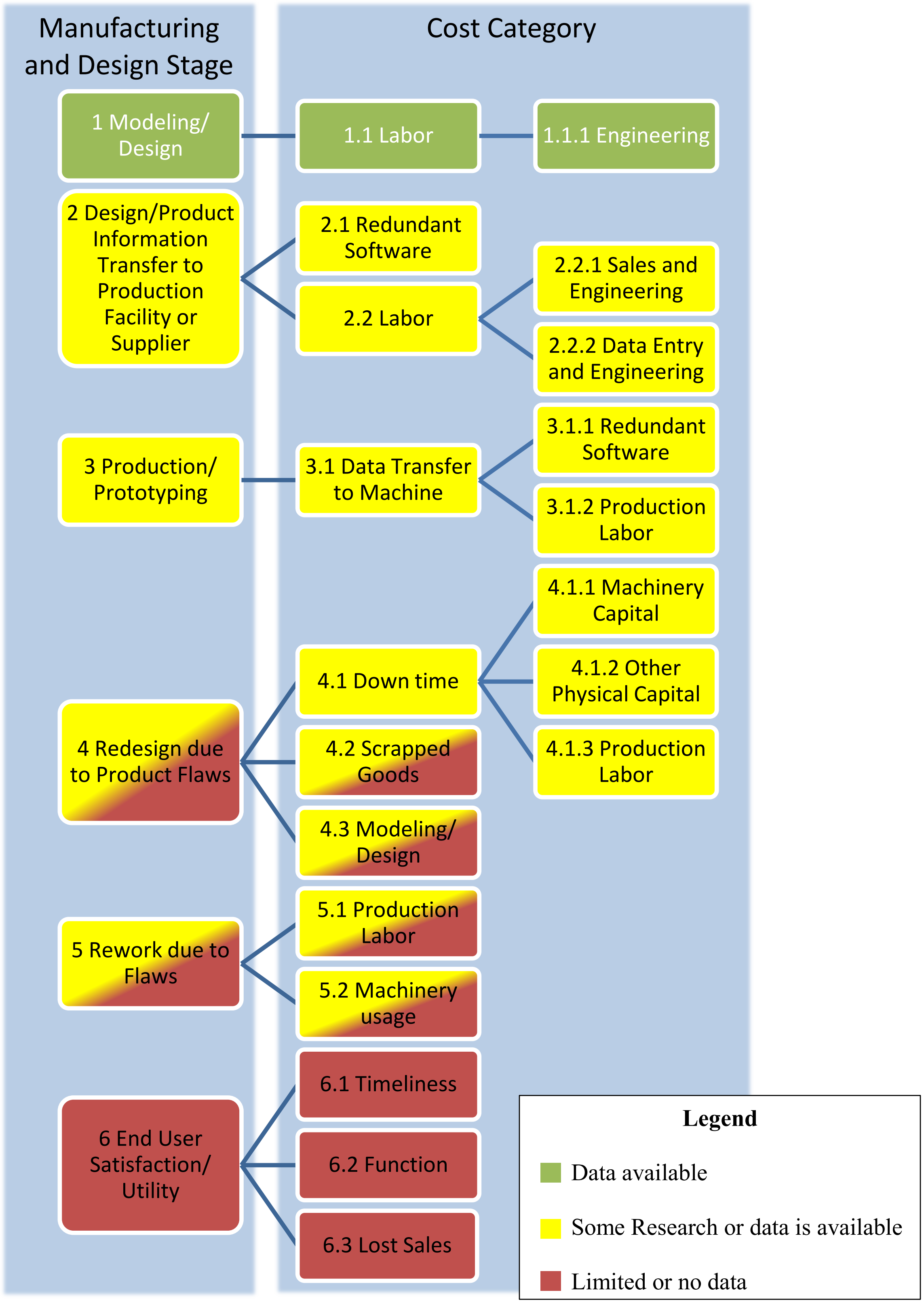

Figure 5.2: Manufacturing Costs Affected by Model Based Enterprise: Product Oriented

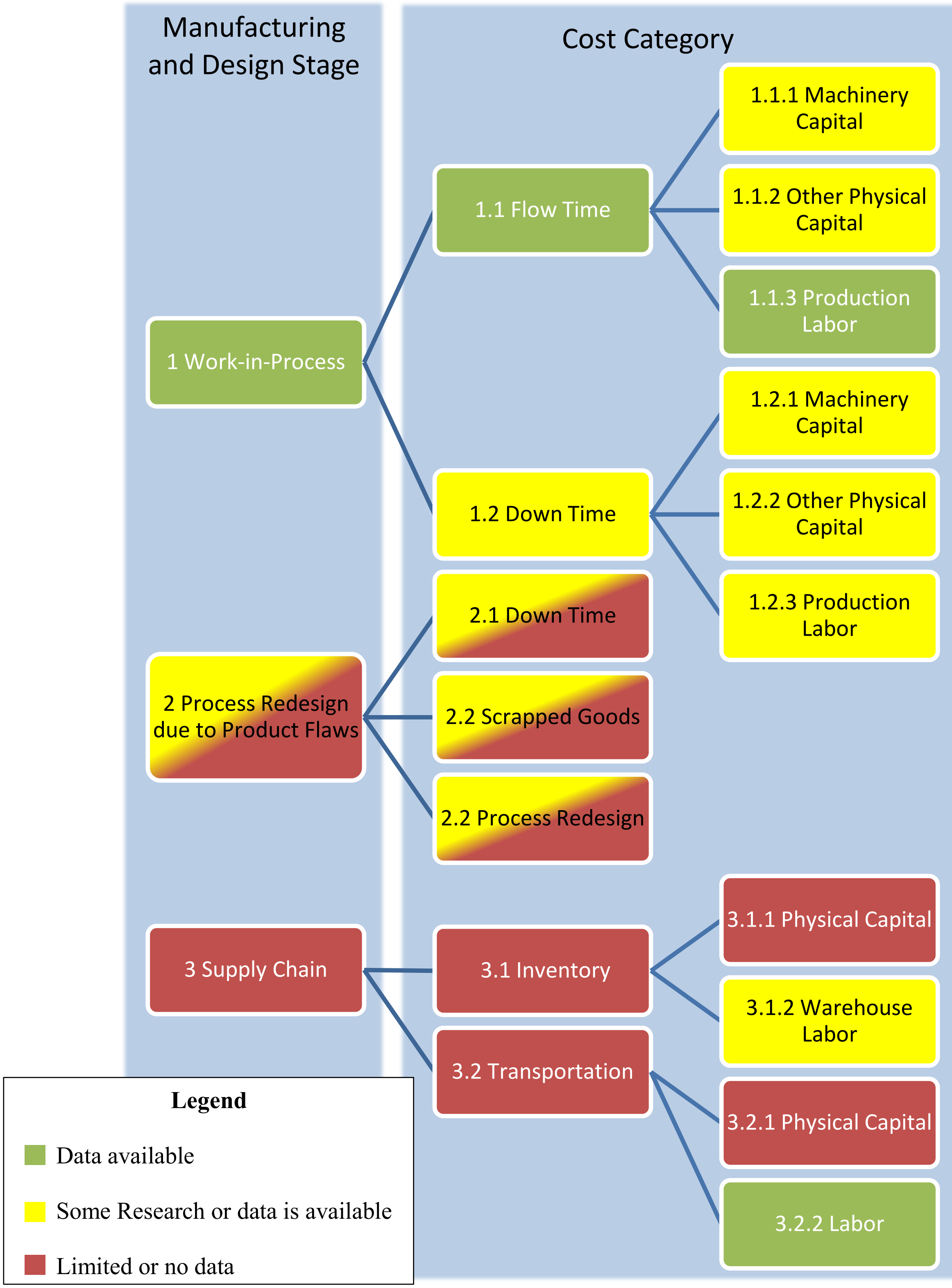

Figure 5.3: Manufacturing Costs Affected by Model Based Enterprise: Process Oriented

from Figure 5.3 but no explicit data was identified in the literature. Given the more complex nature of this cost stage and limited tracking, it is not clear whether it would be incorporated into the estimates.

Models could also be applied to the supply chain, including warehousing. No explicit data was identified in regard to this cost with the exception of labor data from the Occupational Employment Statistics from the Bureau of Labor Statistics.

6. Potential Methods for Data Collection and Analysis

In order to estimate costs/losses relevant to modeling, some data collection via survey is necessary. Section 6.1 discusses using "decomposition" for collecting and analyzing data and Section 6.2 discusses the necessary sample size for an analysis.

6.1. Decomposition

As previously mentioned, this report focuses on problem-based cost categories and aims to gather and report data in a disaggregated component form such as those categories in Figure 5.2 and Figure 5.3. Gathering component data and aggregating it is a method referred to as "decomposition."[30] The challenge of gathering disaggregated cost components is that it requires far more questions to be asked, which can reduce the number of respondents in a survey. The benefit is increased accuracy and increased knowledge of the details.

The increase in accuracy from disaggregating is dependent on the form of the decomposition. For example, consider research on how many hours per year people spend driving. A decomposition of this question could result in the following subcomponents to estimate the final value:

1. How many hours per work day do you spend driving to/from work?
2. How many hours per work day do you spend driving to/from other locations?
3. On average, how many days do you work?
4. How many hours per non-work day do you spend driving?
5. How many road trips do you take per year?
6. How many hours of driving do you spend on road trips?

A survey might ask other questions about driving habits, but the idea is that respondents are better able to answer questions about the components than about the total (e.g., hours per year spent driving).[31] It is important to note, that the form of the decomposition impacts the accuracy. For instance, a set of alternative subcomponents for estimating the hours per year spent driving could include:

1. How many hours per day do you spend sitting at red lights and stop signs?
2. How many hours per day do you spend driving on interstates and highways?
3. How many hours per day do you spend on non-highway roads?

These categories do not aid in estimating the total hours driving per year, as few individuals know how much time they spend on different roads and at stop lights. Moreover, this decomposition is not useful in increasing accuracy. Accuracy can also be increased by using multiple decompositions resulting in more than one estimate.

[30] MacGregor, Donald G. "Decomposition for Judgmental Forecasting and Estimation." In Armstrong, J. Scott. Principles of Forecasting: A Handbook for Researchers and Practitioners. (Norwell, MA: Kluwer Academic Publishers 2001): 107-123.
[31] MacGregor, "Decomposition for Judgmental Forecasting."

The decomposition for collecting data on costs/losses impacted by modeling would use the categories in Figure 5.2 and Figure 5.3. Proportions of each would be used to estimate those portions relevant to modeling. To measure impacts on physical capital, questions would focus on reduced flow time and down time. Costs from this information would be estimated using data from the Annual Survey of Manufactures.

6.2. Required Sample Size for Data Collection

The accuracy and applicability of a collection of data depends on having an adequate sample size. Sample size for manufacturing machinery maintenance was examined in NIST AMS 100-18.[32] The following discussion is, largely, adapted from that report.

There are 54 022 establishments in NAICS 333-336. A required sample size is influenced by many items, including the margin of error and population size. This study is, generally, estimating the mean of a population, which can be represented as:[33]

$$Sample\ Size = \left(\frac{z\sigma}{e}\right)^2$$

where
σ = Standard deviation
e = Margin of error
z = z-score

The 2016 Annual Survey of Manufactures estimates the total value for "purchased data processing and other purchased computer services" was \$5.9 billion for 291 543 establishments with a sample size estimated at approximately 50 000, resulting in a standard deviation of \$13 554, as calculated by:

$$\sigma = \frac{RSE}{100} * \frac{PPS}{EST} * \sqrt{SPL}$$

where
RSE = Relative standard error from the Annual Survey of Manufactures
PPS = Purchased data processing and other purchased computer services from the Annual Survey of Manufactures
EST = Number of establishments in manufacturing from the County Business Patterns data
SPL = Approximate sample size of the Annual Survey of Manufactures

Assuming a 10 % margin of error and a 90 % confidence interval (i.e., z = 1.96), a sample size of 122 is sufficient. Figure 6.1 graphs the various sample sizes required at different confidence intervals and margins of error with the standard deviation equaling

[32] Thomas, "The Costs and Benefits of Advanced Maintenance."
[33] NIST. Engineering Statistics Handbook. Sample Sizes. http://www.itl.nist.gov/div898/handbook/prc/section2/prc222.htm

$13 554 calculated from Annual Survey of Manufactures data. With a margin of error of 20 % and a confidence interval of 90 %, as few as 31 samples are needed.

Since the assessment of sample size relies on a number of assumptions, a probabilistic sensitivity analysis was conducted using Monte Carlo analysis. This technique is based on works by McKay, Conover, and Beckman (1979) and by Harris (1984) that involves a method of model sampling.[34,35] It was implemented using the Crystal Ball software product (Oracle 2013), an add-on for spreadsheets.

Specification for a Monte Carlo analysis involves defining which variables are to be simulated, the distribution of each of these variables, and the number of iterations performed. The software then randomly samples from the probabilities for each input variable of interest. The population, value of "purchased data processing and other purchased computer services," relative standard error, sample size from the Annual Survey of Manufacturers, and the samples size needed for this study were each varied using a triangular distribution with the parameters shown in Table 6-1. This distribution is used since it allows for proportional increases and decreases in variables and the true distribution is unknown. The z-score was varied between a 90 % confidence interval and a 99 % confidence interval. These variations allow for relatively large error in the

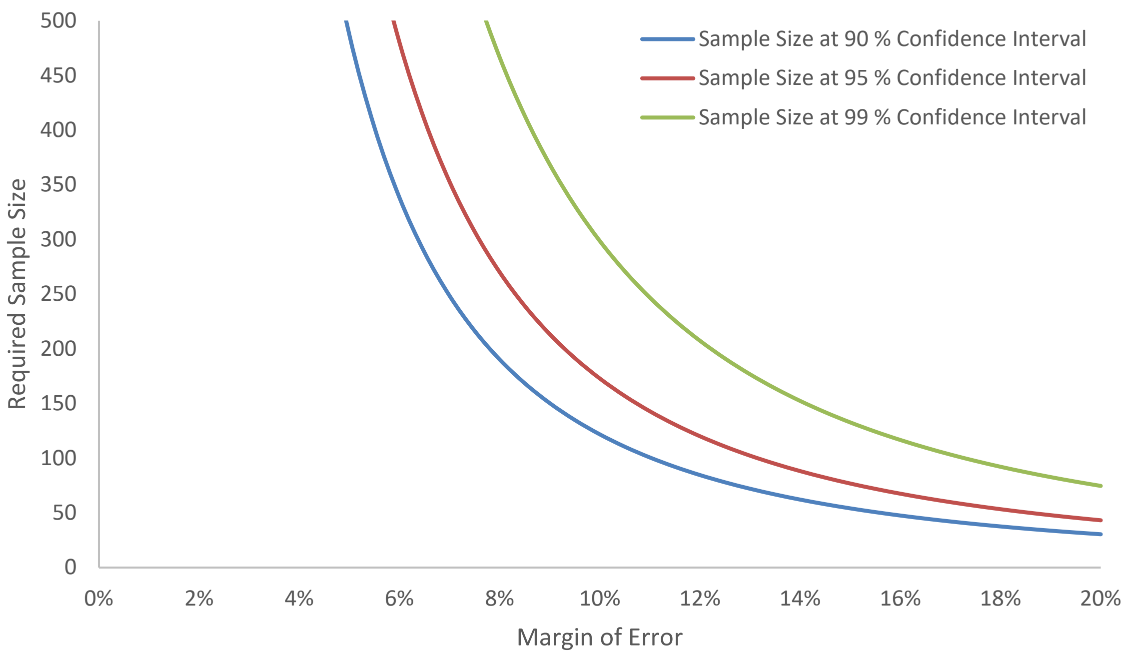

Figure 6.1: Required Sample Size by Margin of Error and Confidence Interval

Note: Standard deviation equals 13 554, as calculated from the Annual Survey of Manufactures

[34] McKay, M. C., W. H. Conover, and R.J. Beckman. "A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code," Technometrics 21, (1979): 239-245.
[35] Harris, C. M. Issues in Sensitivity and Statistical Analysis of Large-Scale, Computer-Based Models, NBS GCR 84-466, Gaithersburg, MD: National Bureau of Standards (1984).

assumptions for calculating the sample size and margin of error, as the standard deviation for "purchased data processing and other purchased computer services" cost ranges from a little less than 7000 to a little more than 76 000.

A cumulative probability graph of the results is shown in Figure 6.2, which shows that for 80 % (i.e., a cumulative probability of 0.80) of the iterations the margin of error is below 0.52 (+/-52 % in estimating the cost of "purchased data processing and other purchased computer services"), as illustrated with doted lines in the figure. Figure 6.3 graphs the margin of error for those iterations in the Monte Carlo analysis that are at the 90 % confidence interval. As seen in the figure, the standard deviation has significant impact on the margin of error; thus, the accuracy of the assumptions has a substantial effect.

Table 6-1: Assumptions for Monte Carlo Analysis (Triangular distributions)

	Min	Most Likely	Max
Population (establishments)	247 812	291 543	335 274
Value of Purchased Data/Processing ($Million)	5301.6	5890.7	6479.8
Relative Standard Error	0.2	0.2	1.5
Sample Size (ASM)	40 000	50 000	55 000
Sample Size (Needed)	20	50	150
z-score (uniform distribution)	1.65	-	2.58

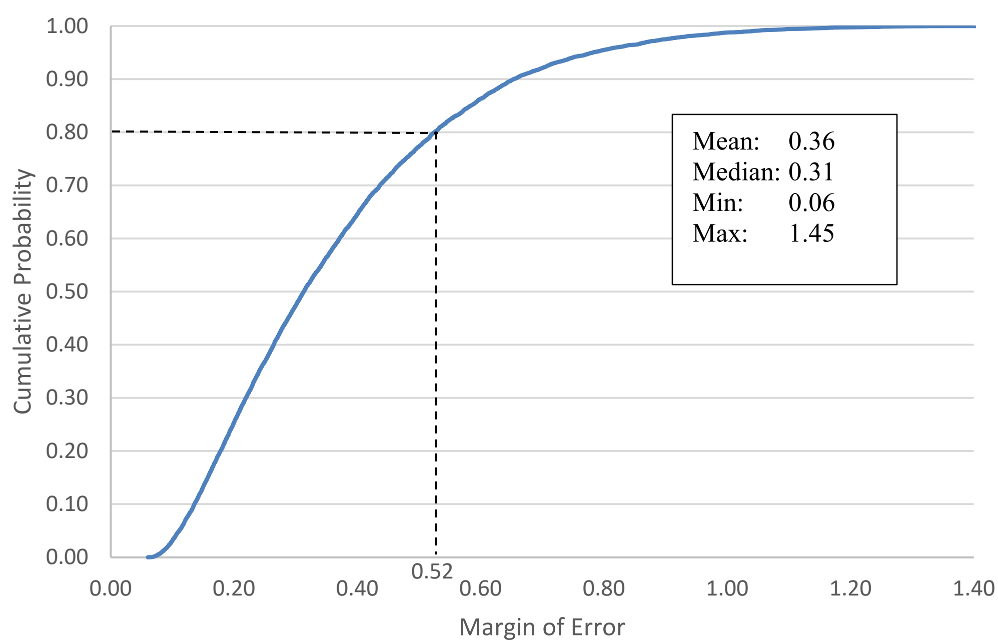

Figure 6.2: Cumulative Frequency Graph, Monte Carlo Analysis

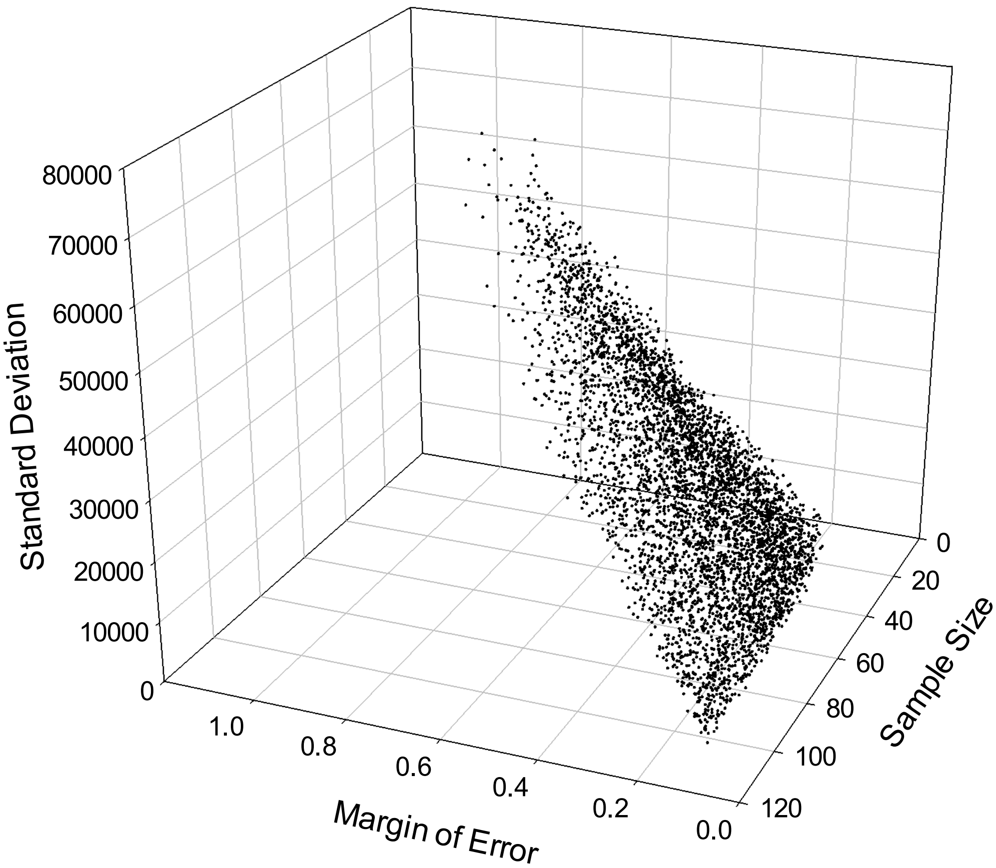

Figure 6.3: Margin of Error Graphed with Standard Deviation of "purchased data processing and other purchased computer services" Cost and Sample Size from Monte Carlo Analysis (90 % Confidence Interval only)

To collect data on costs/losses relevant to inadequate modeling and designs, an estimated minimum sample size of 31 would be needed. This is calculated with a 90 % confidence interval and a 20 % margin of error. A margin of error of 10 % would require a sample size of 122.

7. Summary and Conclusion

Currently, problem-based data relevant to suboptimal designs and models broken into its subcomponents is not available publicly. However, some estimates from data collected at more aggregated levels is available in the literature. Aggregated data has a risk of decreased accuracy and frequently has less usefulness in identifying opportunities for improving efficiency.

PMI embedded 3D models are not widely adopted for product designs, as only an estimated 26.8 % of survey respondents had 51 % or more of their designs released with PMI-embedded 3D models. Some research suggests that this type of modeling data can reduce redundant activities. These costs include an estimated $8.40 billion spent on engineers answering questions and creating additional drawing documentation and $3.84 billion for machinists to do the same. Another study estimates the savings from managing digital data streams through models (CAD models including material characteristics, simulation models of part creation and plant layout, and rapid automated costing functions) to be $8.9 billion and an additional $10.3 billion can be saved through seamless transmission of digital information (wireless transmission of data, seamless integration of sensors, interoperability between CAD/CAM platforms, secure data transmission, advanced data analysis/interpretation, predictive maintenance, and cloud computing). These items, however, include categories of costs beyond modeling.

To collect data on costs/losses relevant to inadequate modeling and designs, an estimated minimum sample size of 31 would be needed. This is calculated with a 90 % confidence interval and a 20 % margin of error. A margin of error of 10 % would require a sample size of 122.

Acknowledgments

The author wishes to thank all those who contributed so many excellent ideas and suggestions for this report. Special appreciation is extended to Boonserm Kulvatunyou of the Engineering Laboratory's Systems Integration Division for his technical guidance, suggestions, and support. Special appreciation is also extended to David Butry and Anand Kandaswamy of the Engineering Laboratory's Applied Economics Office for their thorough reviews and many insights. The author also wishes to thank Nicos Martys, Materials and Structural Systems Division, for his review.

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Appendix A: Percent of Survey Respondents by Groupings from the Model Based Enterprise Report