Predicting Manufacturing Performance of New Radar Subassembly Designs

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Submitted to the Sloan School of Management and the Department of Electrical Engineering/Computer Science in Partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration
Master of Science in Electrical Engineering/Computer Science

In Conjunction with the Leaders for Manufacturing Program at the
Massachusetts Institute of Technology
June 2003

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Abstract

New high-performance radar designs are characterized by precise mechanical components and subassemblies tested to tight electrical performance specifications, typically pushing state-of-the art in advanced materials and manufacturing processes. These designs are often well into the production process before manufacturing system performance can be predicted with confidence.

This work investigates methods to improve the product development process for new radar subassemblies at Raytheon Company, with the goal of better predicting manufacturing system performance earlier in the development process. Subassembly A, a new radar subassembly transitioning into production at Raytheon's Andover, Massachusetts facility, was used as a case study.

It was found that manufacturing process simulations already in use at Raytheon are effective in modeling the structure of complex processes associated with production of radar subassemblies. However, inputs to these models are often inaccurate, in particular first-pass yields at various inspection points in the system. Further it was determined that more accurate first-pass yields required a better understanding of process capability. This, in turn, required better understanding of the subassembly's critical parameters and their allowed variations, so that process capability could be calculated.

The thesis proposes that adding the identification of Key Characteristics (KC) to the product development process will enable better predictions of first-pass-yields which in turn increases the accuracy of manufacturing process simulations. Results are presented for the application of these methods to Subassembly A.

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Acknowledgements

I wish to acknowledge the Leaders for Manufacturing (LFM) Program for its support of this work.

I would like to thank Raytheon Company for sponsoring this work through its partnership in the LFM program. In particular, I would like to thank Roger Hinman, project supervisor, and Ed Verryt, project champion.

My advisors, Dr. Whitney and Prof. Eppinger offered valuable guidance and insight during my internship at Raytheon and when writing the thesis.

I dedicate this thesis to my wife Maha and children Linda and Nadia, who were all on board for a move to Boston and a life-changing adventure called the LFM program.

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Section 1: Introduction

1.0 Overview

Radar system designs have become increasingly capable, largely driven by advances in electronics and software. Higher performance system designs also bring manufacturing challenges. As an example, one key to higher radar performance is higher operational frequencies. This requires better performance from the basic electromechanical subassemblies that guide and shape the electromagnetic waves. Higher frequencies mean scaling down the mechanical dimensions and increasing the precision of such subassemblies.

Raytheon Company is a leader in the development and manufacture of new radar systems, and historically has found it problematic to predict full-rate manufacturing system performance with desired precision for new critical subassembly designs, especially those involving new materials, products and processes that all challenge state-of-the-art. This work proposes that Raytheon can achieve better predictability of manufacturing system performance through improvements in its product development process.

This challenge was addressed in the context of Subassembly A, a critical radar subassembly in the process of transitioning to full-rate production. Prior work had been done to simulate the manufacturing processes for this assembly. These models require inputs of first-pass yield numbers at inspection points in the system. Better accuracy in these inputs requires a better understanding of process capabilities, specifically for those features that have the greatest impact on product performance. This led to a focus on Key Characteristic (KC) identification as an enabler for improving first-pass yield estimates for these designs; and in turn, more accurate manufacturing process simulations.

1.1 Organization of the Thesis

This thesis is organized in sections, first covering the background and project setting, including a more detailed description of the problem and applied approach. A review of the literature discusses KC identification, process capability, and the influence of manufacturing yield on process performance. Results of KC identification for Subassembly A are presented, followed by a section that relates an example of how KCs helped focus the design process. The thesis then returns to the prediction of first-pass yields for manufacturing system models. The culture and environment for change are discussed, and conclusions summarized.

Section 2: Project Background and Description

2.0 Section Overview

This project was conducted as an internship assignment through MIT's Leaders for Manufacturing (LFM) program and sponsored by the Raytheon Company at their Andover, Massachusetts site. This section will discuss this setting, with a brief introduction to Raytheon as a company, specifics on the background and motivation for the project, a definition of the problem and a description of the approach.

2.1 Raytheon Company

Raytheon Company is a leading supplier of government and defense electronics, with other business areas in commercial electronics, business aviation, and special mission aircraft. Headquartered in Lexington, MA, Raytheon has 77,500 employees worldwide and $16.9 billion in 2001 revenues. Dan Burnham from Allied Signal was appointed CEO in 1998, and launched the Raytheon Six Sigma (R6σ) program, an aggressive initiative to establish a company-wide culture that includes a mix of best practices. This initiative is discussed in Section 7.3 in the context of organizational change.

Raytheon and other defense contractors face a changing industry environment. Competition has increased. Mergers and acquisitions over the past few years have resulted in fewer, but stronger players in the market. The US government is demanding more accountability and encouraging the use of more commercial practices. As an example, the Undersecretary of Defense recently emphasized the use of a Spiral Development process focusing on continued evolutionary product enhancements using relatively short run product/process evaluations rather than on long-term ongoing production of a continually maturing design[1].

2.2 Integrated Defense Systems (IDS) Andover Operations

This internship was hosted at Raytheon's Andover, MA facility from June through December 2002. During this time, in October 2002, Raytheon announced a major reorganization of its government and defense businesses into seven new business units. The Andover facility is now the Operations center for the newly organized Integrated

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[1] E.C. Aldridge, "Evolutionary Acquisition and Spiral Development," US Department of Defense Memo dated April 12, 2003.

Defense Systems (IDS) business unit. It is one of Raytheon's major manufacturing centers, a 1.2 million ft^2 facility with approximately 3,000 employees. The site is characterized by a diverse array of capabilities including commodity manufacturing centers such as circuit card assembly and metal fabrication, as well as more specialized activities such the manufacture of microwave subassemblies and integration of surface radar systems. As an example of a surface radar system manufactured in the Andover plant, readers may be familiar with the Patriot system that received extensive coverage during the Gulf War and operation Iraqi Freedom. The next generation of surface radars employing enhanced state-of-the-art Active Electronically Steered Array (AESA) technology is actively under development by Raytheon. Further information on this and other radar programs can be found on Raytheon's website[2].

2.3 Surface-Based Radar Systems and Subassemblies

This project deals with achieving predictability in the manufacture of newly designed precision subassemblies for surface-based radar systems, including large phased-array radars used for missile defense. Raytheon is a leader in the design and production of such systems, often working together with other firms to supply sophisticated large-scale solutions.

Even in full production, large phased-array radar systems are low-volume items, with perhaps only a few of any given system built in a year. However, manufacturing volumes of some subassemblies within the system are much higher. In particular, the front end of the antenna for a phased-array radar system may contain many thousands of identical elements. In an environment accustomed to low-volume production these relatively higher volumes present a manufacturing challenge.

This thesis work is done in the context of analyzing one of these relatively high volume subassemblies that comprise the front end of a large surface-based phased-array radar system. The particular subassembly studied will be called "Subassembly A".

2.4 Subassembly A

Subassembly A provides an excellent case study for this thesis work. As a new design undergoing the transition to production, it was found that manufacturability issues required

[2] http://www.raytheon.com

a significant redesign effort. At the start of the internship, this redesign was complete, and Subassembly A was ready for transition to production, with a "Proof of Design" run of 75 subassemblies already underway. These first 75 units were built in an engineering development lab with the cooperation of both product and process design engineers.

The process was then transitioned to the manufacturing floor, where an additional 200 assemblies were built by the unionized hourly work force as part of a "Proof of Manufacturing" run, under the close supervision of process development engineers. This work was completed in late fall and production began ramping to a full-rate goal of 240 subassemblies/day, reaching approximately 50 subassemblies/day by the end of the internship in December 2002. Over 20,000 Subassembly A units are required per radar system.

In addition to high volumes relative the overall system, these subassemblies have the following characteristics that challenge the development of production processes, and make it difficult to predict how well a proposed manufacturing system will perform:

- Aggressive microwave radio frequency (RF) electrical performance specifications, with performance targets at or near the limit of present process capabilities.
- Tight mechanical tolerances, typically on the order of .001"
- Assembly processes requiring many accurate special-purpose fixtures
- Specialized materials and joining processes

2.5 Project Motivation

The product clockspeed of new radar systems and subassembly designs is quite slow, with new development projects typically separated by many years[3]. Each time a new radar system subassembly is transitioned into production at the Andover plant, the Surface Radar Operations group faces the challenge of predicting manufacturing system performance for the new design. Particularly for the higher volume subassemblies, basic manufacturing system performance parameters such as first-pass yield have a significant impact on cost and schedule. This project was motivated by the desire to look at this transition first-hand in the context of Subassembly A, and recommend improvements enabling better predictability for this and future such design efforts.

[3] Charles H. Fine, *Clockspeed: Winning Industry Control in the Age of Temporary Advantage* (Reading, Massachusetts: Perseus Books, 1998).

2.6 Problem Statement

This research proposes improvements to the product development process for these high-volume subassemblies for radar systems. This includes the concurrent engineering of product, manufacturing system processes, and supply chain. The goal is to develop a method and tools to predict manufacturing systems performance measures earlier in the product development process rather than waiting until well into full-rate production—when changes to product and processes have a much more significant impact on cost and schedule. As shown graphically in Figure 1, the intent of these predictions is to enable better strategic business decisions.

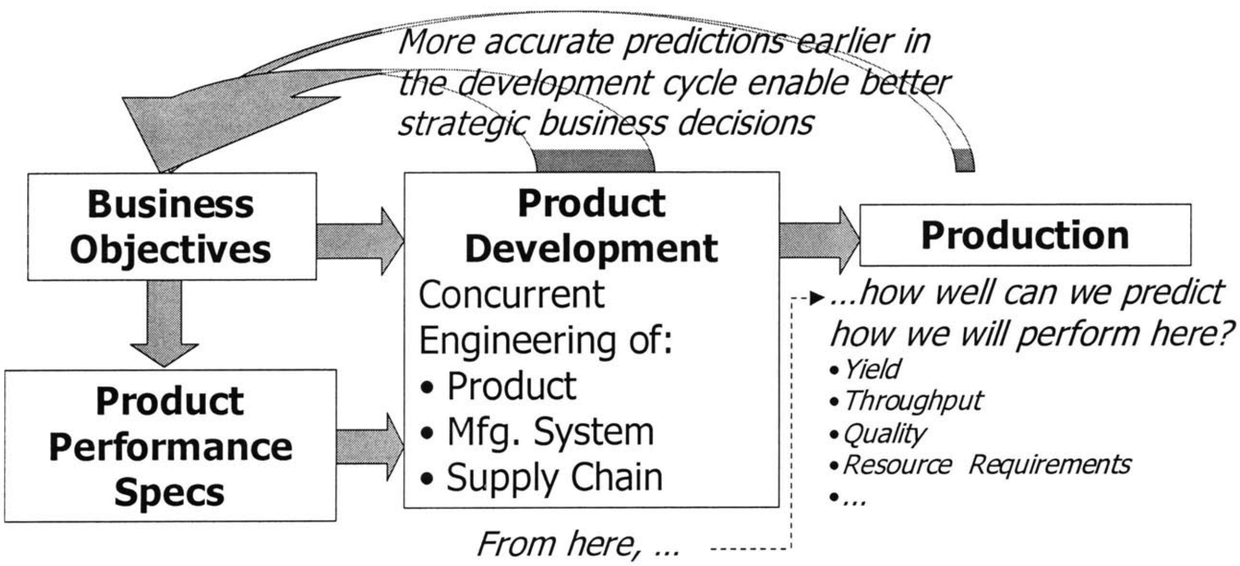

Figure 1: Earlier Feedback Enables Better Strategic Business Decisions

2.7 Project Approach

A plan to predict manufacturing system performance was developed in the context of evaluating Subassembly A's transition into production. The approach involved first becoming familiar with the materials, assembly processes, performance specs and test methods for this subassembly. Industry practices were investigated and a literature survey conducted on topics related to predicting manufacturing performance during the product development process. Project milestones and a schedule were created early in the project. This plan is depicted graphically in Figure 2.

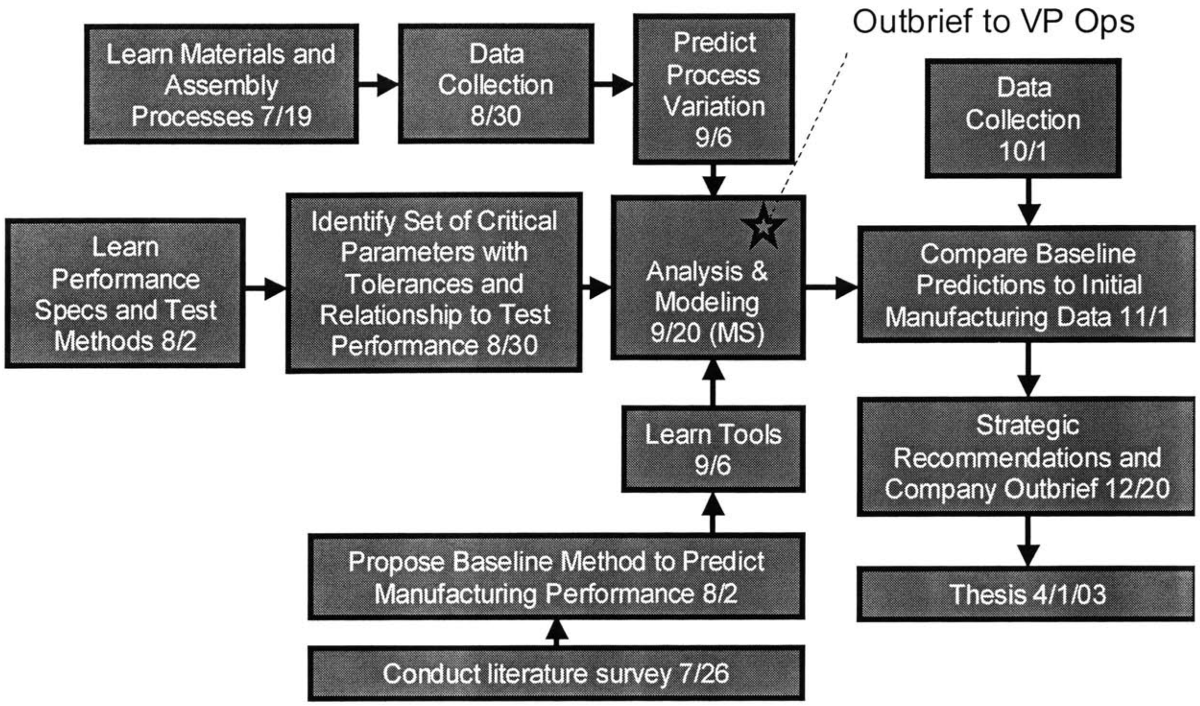

Figure 2: Project Milestones and Schedule

Early project work involved evaluating the use of manufacturing process modeling software introduced at Raytheon-Andover by a prior LFM intern[4]. This software was found to be effective in visually representing and modeling complex manufacturing process environments. Based on interviews with those using the models, it was found that accuracy was limited, due mainly to the accuracy of input data. The project was then focused on identifying the most important enablers for more accurate manufacturing system models, starting with immediate causes, and following the method of "5 Whys," a classical quality improvement tool used for getting to the root of a problem.

In this project the first why could be phrased as, "Why are Raytheon's manufacturing system simulation models sometimes lacking desired precision in predicting manufacturing performance?" While there are multiple answers to this question, investigating Subassembly A's transition into production highlighted one important direct cause: "Inaccuracy in first-pass yield numbers that are required inputs to the model." Asking why again helps reveal contributing causes. Here, the answer to "Why are first-pass yield

[4] Timothy J. Sweitzer, "A Simulation-Based Concurrent Engineering Approach for Assembly System Design" (Master's thesis, Massachusetts Institute of Technology, 2002).

estimates inaccurate?" uncovers the most significant contributing cause: "Not knowing which process steps are the most important determinants of first-pass yields."

Further whys reveal lower level contributing causes. In this case, asking, "Why do we not know which process steps are the most important to yields?" leads to the cause: "Not knowing which product and process features at risk to variation have the most significant impact on customer-required performance." Industry has come to call such features *Key Characteristics (KCs)*. And, "Why do we not know the KCs for new radar subassembly designs?" Because the identification, verification, and communication of KCs is not well embedded within Raytheon's product development process for radar subassembly designs.

This series of questioning led to the focus of this project on developing a chain of enablers for better predictability in the development process for new radar subassembly designs at Raytheon. Starting from defined performance requirements and tolerances, the three main elements of this "predictability chain" are shown here in Figure 3. The product and process attributes that are the major drivers of performance are identified and performance variation calculated. This variation is compared with tolerances, and allocated to KCs. Process capability can be expressed in terms of capability indices such as Cpk. This allows prediction of first-pass yield, the percentage of total units that pass a given test or inspection the first time. Note that this diagram does not imply that these are the only enablers necessary to accurately predict manufacturing performance, but rather that these were felt to be most important in the limited context of this project and thesis.

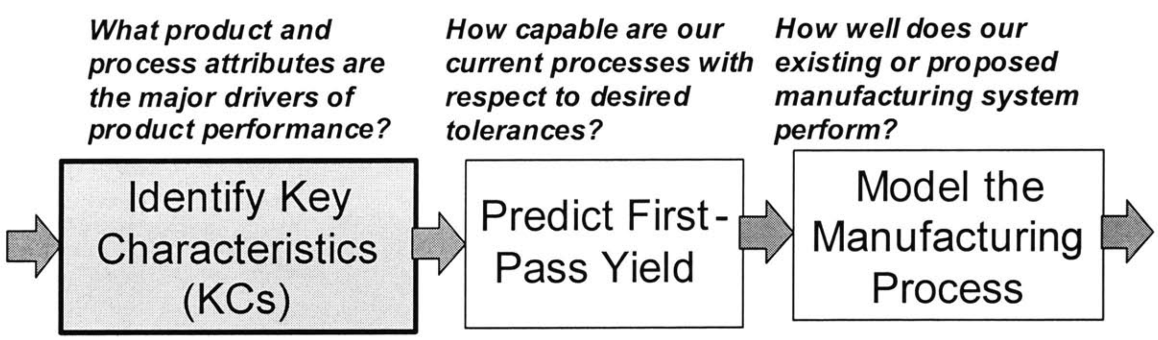

Figure 3: Elements of Predicting Manufacturing System Performance

A significant portion of the internship was spent investigating Raytheon-Andover's present capabilities in each of the areas shown in Figure 3. It was found that a number of tools and methods are already being applied in the second and third areas. The area identified with the greatest potential for improvement is the first: Identification of KCs, shown highlighted in Figure 3 above. Thus KCs became a focus area of this work. This is a root-cause enabler for better first-pass yield predictions and manufacturing system modeling because it enables impacts on product performance to be identified.

Section 3: Identification of Key Characteristics (KCs)

3.0 Section Overview

Accurately predicting how well a product design can be manufactured involves first understanding sources of variability in product and process features and then understanding how this variation impacts the performance required of the product. Radar subassemblies are typical of complex system assemblies, with many product and process features impacting the performance of the product.

Prioritizing which of these parameters have the greatest impact on required performance and are at risk due to variation with respect to tolerances is the first step to predicting how well the product can be manufactured. This topic has been termed identification of Key Characteristics (KCs). This section discusses KCs, looking at definitions and applications in industry and specifically at the their use within Raytheon. The following section will then present a KC identification exercise for Subassembly A.

3.1 What is a KC?

Many manufacturing firms have recognized the importance of identifying what they have termed key, critical, or important characteristics or parameters. Since the 1980's several major US companies have drafted specific guidelines and documents defining methods to capture and communicate this information as part of the product development process. While there are some differences in the definitions and terminology that have been proposed, there are common themes. Thornton suggests a definition that is a hybrid of definitions used by leading industry firms:

> Key Characteristics are the product, subassembly, part, and process features that significantly impact the final cost, performance, or safety of a product when the KCs vary from nominal. Special control should be applied to those KCs where the cost of variation justifies the cost of control.[5]

[5] A.C. Thornton, "A Mathematical Framework for the Key Characteristic Process," *Research in Engineering Design* (1999) 11:145-157.

It is worth noting that a feature may be important to performance, but if variation is not significant when compared to tolerances, these features should not be classified as KCs. Instead they may be said to be important features that are under control.

The concept of a loss function is often used to describe the selection of KCs. That is, if we imagine plotting loss in performance as a function of a product feature, characteristics are considered key when there is a steep loss in performance as the feature moves away from its target value and approaches specified limits. Features are not considered key where the loss in performance is relatively flat as we move away from nominal within the specified limits. Taguchi describes this as a *Quality Loss Function* and suggests that it can be estimated as a simple quadratic function where loss of quality increases as the square of the deviation from nominal[6].

As suggested in the definition above, KCs are often categorized by type. Lee and Thornton suggest three fundamental categories[7]:

- *Product Key Characteristics (PKCs)* are associated with the important physical properties or product features that impact customer required performance. These are permanent for a given product design decomposition and set of requirements.
- *Assembly Process Key Characteristics (AKCs)* are the features during each assembly stage on the product, tool, fixture or procedures that significantly affect the realization of a product KC at the next-higher assembly process level. These are permanent for a given assembly process and product design decomposition.
- *Manufacturing Process Key Characteristics(MKCs)* are the manufacturing machine process parameters and/or fixturing features for machine tools and equipment that significantly affect the realization of a product or an assembly process key characteristic at the detailed part feature level. These are permanent for a given manufacturing process and product.

3.1.1 Primary KCs

The identification of KCs starts when customer requirements are translated into top-level preliminary engineering specifications. Ulrich and Eppinger[8] describe this process.

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[6] Genichi Taguchi and Don Clausing, "Robust Quality," *Harvard Business Review* (1990) 68(1): 65-75.
[7] D.J. Lee and A.C. Thornton, "The Identification and Use of Key Characteristics in the Product Development Process," *Proceedings of the 1996 ASME Design Engineering Technical Conferences and Computers in Engineering Conference* Irvine, California, August 18-22, 1996.

It starts by preparing a list of metrics associated with customer needs. A target, or ideal specification, is set for each metric. Recognizing that some amount of variation is inescapable, designers then assign tolerances around these targets to insure that the range of acceptable performance is not exceeded.

Primary KCs are those product features where the amount of variation with respect to tolerances has a direct and significant impact on customer requirements. Primary KCs must be met as they are directly based on customer requirements.

3.1.2 Derived KCs

The development of complex systems typically follows an approach where system architecture is defined and then requirements flowed down to lower levels such as subsystems, assemblies, and parts. Grady provides a classic text describing this process[9]. KCs require a similar flowdown process.

A *Derived KC* is a parameter where variation significantly contributes to variation in a higher-level KC. Primary KCs are thus dependent on many derived KCs. The assembly KCs described above are considered derived KCs. They are permanent for a given decomposition, physical realization, or chosen design. But different designs aimed at the same primary KCs will have different derived KCs. From the perspective of the design process, primary KCs *must* be met. However, in evaluating design alternatives, derived KCs can be viewed as a *tool* to understand and manage how variation at lower level parts and assemblies combines to create variation in customer-required performance.

3.2 Resources and Tools for Identifying KCs

Identification of KCs is a process of understanding how various product and process features impact product performance, then selecting those features that have the greatest impact on performance and are at risk due to variation. How these features are identified and communicated varies across industry. Thornton describes some of these methods of KC identification in the context a Variability Risk Management (VRM) framework[10].

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[8] Karl T. Ulrich and Steven D. Eppinger, *Product Design and Development,* 2nd ed. (New York: McGraw-Hill, 2000), 79-102.
[9] Jeffrey O. Grady, *System Requirements Analysis*, (McGraw-Hill, 1993).
[10] A.C. Thornton, "More than Just Robust Design: Why Product Development Organizations Still Contend with Variation and its Impact on Quality," *Research in Engineering Design* (2000) 12:127-143.

Primary KC identification begins in the early stages of product development, when customer requirements are translated into system specifications. In this context, the House of Quality, a graphical tool that is part of Quality Function Deployment (QFD), provides a core matrix that is used to relate customer needs to engineering specifications for system-level features. Hauser and Clausing[11] describe the House of Quality and Ulrich and Eppinger[8] provide an example of how this needs-metrics matrix is applied. An alternate method of mapping function requirements in physical design attributes is Axiomatic Design, presented by Suh[12,13]. Further publications and resources on this topic are available from the website for the MIT Axiomatic Design Group[14]. Understanding the relationships between customer needs and engineering parameters provides an opportunity to identify the subset of parameters that are subject to variation and that have the strongest impact on customer performance requirements.

Derived KCs are developed in a flowdown approach. This flowdown may be quite large for complex systems. Thornton cites examples of a 100 part medical product having 600 elements, and a single join in an aircraft having about 25 elements, with different companies using custom flowdown methods and databases[10].

One systematic method is through the analysis of tolerance chains. For the case of mechanical subassemblies, Whitney and Mantripragada describe the Datum Flow Chain (DFC) that relates KCs in assemblies[15,16]. The joints and/or fixture surfaces that define the dimensional constraints between parts of an assembly are represented in directed graphs. These graphs describe the relationship of the lower level features that comprise a given KC. This establishes a basis for understanding how a particular KC is impacted by variation buildup in the assembly features that contribute to it.

Other tools traditionally used in the product development process can assist in the identification of KCs. For example, Failure Modes and Effects Analysis (FMEA) is a

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[11] John R. Hauser and Don Clausing, "The House of Quality," *Harvard Business Review* (1988), 66(3): 63-73.

[12] N.P. Suh, *The Principles of Design*. (New York: Oxford University Press, 1990).

[13] N.P. Suh, *Axiomatic Design: Advances and Applications*. (New York: Oxford University Press, 2001).

[14] http://axiom.mit.edu/

[15] R. Mantripragada and D.E. Whitney, "The Datum Flow Chain: A Systematic Approach to Assembly Design and Modeling," *Research in Engineering Design* (1998) 10:150–165.

[16] D. E. Whitney, R. Mantripragada, J. D. Adams and S. J. Rhee, "Designing Assemblies," *Research in Engineering Design* (1999) 11:229–253

process to identify potential failure modes, describe their effects, determine causes, and take action. Causes of failure due to variation lead to the identification of KCs.

Various design methods can be used depending on applicability of analysis tools and availability of data. If mathematical equation or simulation-based product models can be created, then sensitivity analysis or Monte Carlo simulation can be used to determine performance given variation in parameters. If a mathematical model is not possible, then Design of Experiments can often be applied with good results. Phadke provides a good references for DOEs[17]. Historical data can also be useful, for example in the form of a process capability database.

3.3 Industry Adoption of KCs

3.3.1 Commercial

There are many examples of companies that have adopted the practice of identifying KCs. These include automakers such as GM, Ford and Chrysler, commercial aerospace manufacturers such as Boeing Commercial Airplane Group and Vought, and a variety of other companies including Kodak, ITT, and Xerox [7,10,18]. MIT has been instrumental in coordinating the development of a body of knowledge on KCs and many publications and other good resources including case studies on KCs in industry can be found at MIT websites for Key Characteristic[19], the Variation Risk Management Group at MIT[20] and Prof. Anna Thornton's homepage[21].

3.3.2 Defense

In the defense industry, KC identification has been recognized by the United States government as an important development process method with the potential to reduce development and production costs and delays[22]. As competition increases for development

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[17] Madhav S. Phadke, *Quality Engineering Using Robust Design*, (Englewood Cliffs, NJ: Prentice Hall, 1989).
[18] Boeing Commercial Airplane Group, *Key Characteristics: The First Step to Advanced Quality* Revision A, (Seattle: Boeing Company, 1992)
[19] http://web.mit.edu/afs/athena.mit.edu/org/c/consortia/keychar/
[20] http://variation.mit.edu/
[21] http://web.mit.edu/acthornt/www/
[22] United States General Accounting Office, *Best Practices: Capturing Design and Manufacturing Knowledge Early Improves Acquisition Outcomes*. Report to the Subcommittee on Readiness and Management Support, Committee on Armed Services, U.S. Senate, July 2002.

contracts, Raytheon and other defense contractors will be under increasing pressure to show that their development processes incorporate the effective use of KC identification.

Defense contractors have already begun responding to this trend. For example, in the Department of Defense's *DoD Integrated Product and Process Development Handbook*, Key Characteristics are discussed as a best practice in place at Northrop-Grumman[23]:

> *Key Characteristics (KC)* are designated to identify those part or assembly features/interfaces where variation from nominal results in the greatest loss. Statistical Process Control (SPC) measurements are then focused on key characteristics to minimize variation, ensure capable processes, and reduce unnecessary inspection requirements.

The Best Manufacturing Practices Center of Excellence (BMPCOE), a partnership among the Office of Naval Research's Best Manufacturing Practices and other government, academic, and industry partners, relates a number of case studies where Lockheed-Martin and other defense contractors have implemented KC identification[24]. Following is an excerpt from a case study describing their program:

> ...Lockheed Martin Electronics & Missiles identifies the relatively few high-level critical features of any design. Each of these features, in turn, could have many crucial components contribute to the overall criticality, but the analysis greatly reduces the field of consideration. Once the critical features are identified, variability reduction and the resulting statistical tracking are applied...One result of using this methodology was the invention of a variability reduction flag being incorporated into Lockheed Martin Electronics & Missiles' drawing packages and procurement documentation... This effort provides a substantial benefit to the design process by allowing the original equipment manufacturer to provide input up front. It also greatly reduces the number of Engineering Change Proposals that follow any new design.

Another example is from Lockheed-Martin's Tactical Aircraft Systems F-22 Variability Reduction (VR) program. The BMPCOE case writeup states:

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[23] Office of the Undersecretary of Defense. *DoD Integrated Product and Process Development Handbook*, Washington D.C., July 1998.

[24] *Best Manufacturing Practices Web Site*. Available at http://www.bmpcoe.org/

The VR team on the F-22 has identified 2,561 product key characteristics. These are part-number driven and equate to the 678 processes/part families that led to the development of 126 Variability Reduction Instructions. Lessons learned during this process include the need to incorporate VR into normal engineering requirements to help early identification of key characteristics... No award fee on the F-22 has been lost since the implementation of the VR program.

3.4 Use of KCs at Raytheon

Through interviews and web searches on the Raytheon intranet no evidence was found of any formalized KC identification on the surface radar programs at Raytheon's Andover facility and supporting design centers. It was found that identification of important features and parameters occurs informally as part of the design process, but is not a part of the defined concurrent engineering development plan. It is not yet a required component of design reviews or other process gates, with no commonly applied method of communicating and correlating the relative importance of product and process features on product and manufacturing system design documents such as part and assembly-level technical drawings and process sheets.

However, a company-wide search revealed that KC identification methods have been successfully applied on a few programs at Raytheon facilities in Tucson, AZ, part of Missile Systems, a separate business unit from Integrated Defense Systems (IDS). IDS Operations includes the Andover Manufacturing campus, which was the site of this internship[25].

One noteworthy example of a Raytheon Missile Systems program implementing KC identification is AIM-9X, an air-to-air missile program. This program is cited in a report on best practices to the US Senate Committee on Armed Services[23], which examines five Department of Defense programs and compares program performance indicators of unit cost and production delays [reference here]. Of these five programs, AIM-9X experienced the lowest percentage unit cost increases, only 4% compared to a high of 182% for other programs, and the lowest production delay, only 1 month compared to a high of 39 months for other program. Specifically, "...early identification of key characteristics and critical

[25] phone conversations with Peter Bersbach, contact for Key Characteristics implementation at Raytheon Missile Systems in Tucson (July-December 2003).

manufacturing processes…" is quoted as a distinguishing factor in the success of AIM-9X relative to the other programs studied.

3.4.1 Raytheon Key Characteristics Designation System (KCDS)

Raytheon's Key Characteristics Designation System (KCDS) used in Tucson has its legacy in the 1997 acquisition of Hughes Electronics defense business, a General Motors (GM) spinoff[25]. Its major objective is described as an "aid in the economical manufacture of quality products", and to provide the basis for process control activities. A nine page reference manual defines various terms, concepts and method of application[26]. The remainder of this section is a brief summary from this document.

Two types of key characteristics are described:

- *Key Product Characteristics* (KPCs) are product features for which reasonably anticipated variation could significantly affect either the product's safety or fit/function.
- *Key Control Characteristics* (KCCs) are process parameters for which variation must be controlled around some target value to insure that variation in a KPC is maintained or minimized around its target value.

Key Product Characteristics are identified using the concept of a loss function as described previously. Separate symbols are used on drawings and specifications to indicate either a Fit/Performance KPC or a Safety KPC.

Once KPCs have been identified as either Fit/Performance or Safety, the associated KCCs are identified and control plans designed to insure that process controls are sufficient to minimize variation in KPCs. Three levels of "care" in the manufacturing process are identified:

- *Standard Care* describes the usual and customary practices applied to manufacturing processes so as to meet basic customer requirements.
- *Additional Care* is required in manufacturing processes associated with Fit/Performance KPCs to reduce variation around the target level. This typically consists of identifying a Process Control Plan to reduce variation.
- *Special Care* is required in manufacturing process associated with Safety KPCs.

[26] Raytheon Key Characteristics Designation System, Raytheon internal document

Section 4: KC Identification for Subassembly A

4.0 Section Overview

Subassembly A was taken as a test case for the identification of KCs at a subassembly level. As the internship began, the detailed design of this subassembly was just finishing and the transition to production starting. This section describes the selection of candidate KCs, data collection during pre-production, analysis involving correlation of KC data to performance measures and implications for KC selection.

4.1 Identifying Candidate KCs

Identification of KCs for Subassembly A began in the early stages of its transition into production, with a "Proof of Design" (POD) pre-production run underway. This involved skilled process development engineers from the manufacturing organization working closely with electrical and mechanical design engineers and materials experts to build 75 subassemblies in an engineering development lab. In the absence of a KC flowdown from a higher-level assembly, these design and manufacturing engineers started developing a list of candidate KCs by reviewing part and subassembly drawings. They identified 57 features at risk to variation where such variation was felt to have the greatest impact on performance. Many of these fell in the category of "we think this might be important but we don't really know." Acting as a coordinator, I worked with the team to reduce this initial list.

Tolerance studies and experience to date in building test pieces for the POD run were used to reduce the list of candidate KCs. Tolerance studies had been used to determine allowable upper and/or lower specification limits (USL/LSL) around target parameters. They were performed using finite element analysis software and provided a simulated measure of RF electrical performance for selected variations in parameters. The initial list of 57 was reduced to twelve features that were felt to be most important. This list is given in Table 1, listed roughly in the order of perceived importance to the design community. Analysis was simplified to look at two electrical performance measures, where five of the twelve features primarily impact the first performance measure and the remaining seven primarily impact the second performance measure. Note that generic names for features and electrical performance measures are used to protect Raytheon proprietary information.

Table 1: Candidate Key Characteristics for Radar Subassembly A

Designator	Key Characteristic	Electrical Performance Measure Impacted
KC1	Joint 2 void depth	Electrical Performance 2
KC2	Width near front	Electrical Performance 1
KC3	Width across step	Electrical Performance 1
KC4	% of Joint 1 not flush	Electrical Performance 1
KC5	Coplanarity	Electrical Performance 1
KC6	Substrate height	Electrical Performance 2
KC7	Epoxy on front face	Electrical Performance 1
KC8	Cable protrusion	Electrical Performance 2
KC9	Cable length from island step	Electrical Performance 2
KC10	Height from bottom of island	Electrical Performance 2
KC11	Gap back	Electrical Performance 2
KC12	Gap front	Electrical Performance 2

4.2 Data Collection

The next step in transitioning Subassembly A into production was moving from the engineering development laboratory to the factory floor, and starting a "Proof of Manufacturing" (POM) run. The unionized hourly workforce built 200 subassemblies under the close supervision of the process development engineers and using the process documentation that had been updated based on lessons learned from the POD run.

During the POM run, each subassembly was serialized, and candidate KC features identified were carefully measured and recorded. After assembly, each unit underwent a required RF electrical test. This test data was captured by serial number, then average electrical performance across frequency bands was calculated for each of the two performance measures of interest.

4.3 KC Data Presentation and Analysis

Data presentation and analysis is divided into two subsets according to the two electrical performance measures. Results for Electrical Performance 1 are presented first, with respect to contributing parameters KC2, KC3, KC4, KC5, and KC7. This is followed by results for Electrical Performance 2 with contributing parameters KC6, KC8, KC9, KC10, KC11, and KC12. For KC1, void depth indicates an internal measurement not accessible in the final subassembly. A non-destructive method of evaluating this joint using a high-resolution real-time x-ray system was identified, but this equipment was not available for use in time for completion of this project.

Scatter plots using Microsoft Excel are given separately for performance as a function of each KC. Data and associated specifications have been offset and/or scaled to protect Raytheon proprietary information, but the plots accurately represent the relative variation in measurements and corresponding electrical performance.

4.3.1 KCs Impacting Performance Measure 1

Results for Electrical Performance 1 are presented here, with respect to the following contributing parameters: KC2, KC3, KC4, KC5, and KC7. Scatter plots are shown in Figure 4 through Figure 8, followed by observations.

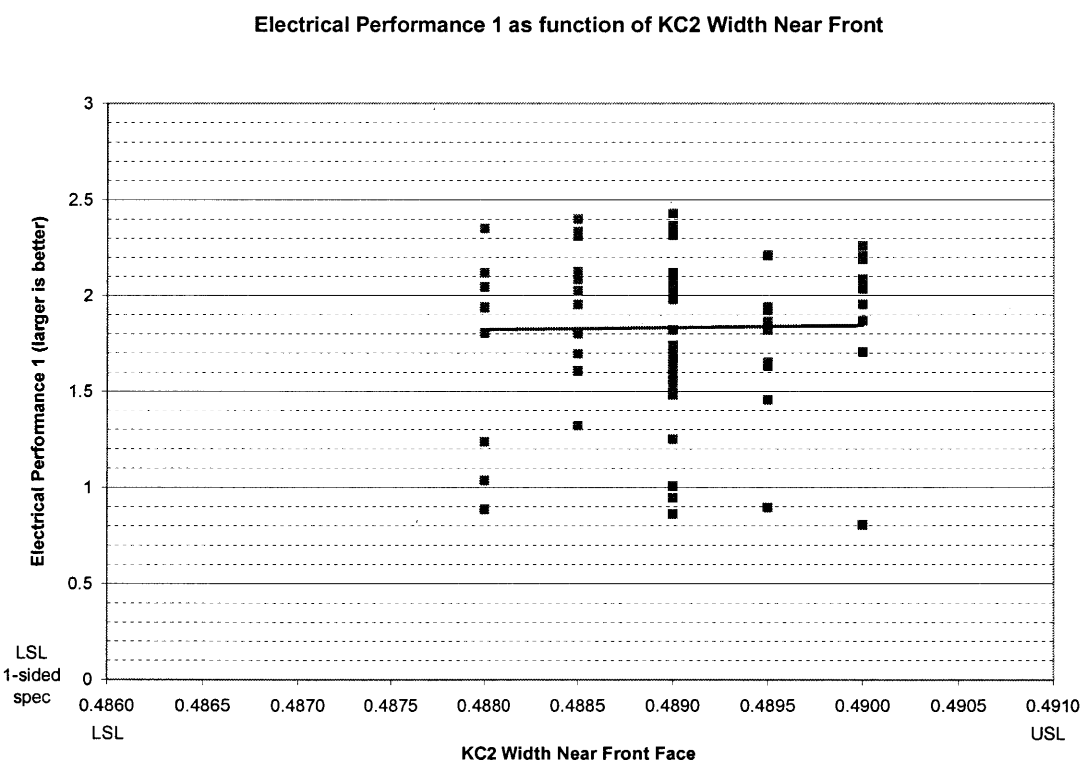

Figure 4: Scatter Plot and Regression Line for KC2 Width Near Front

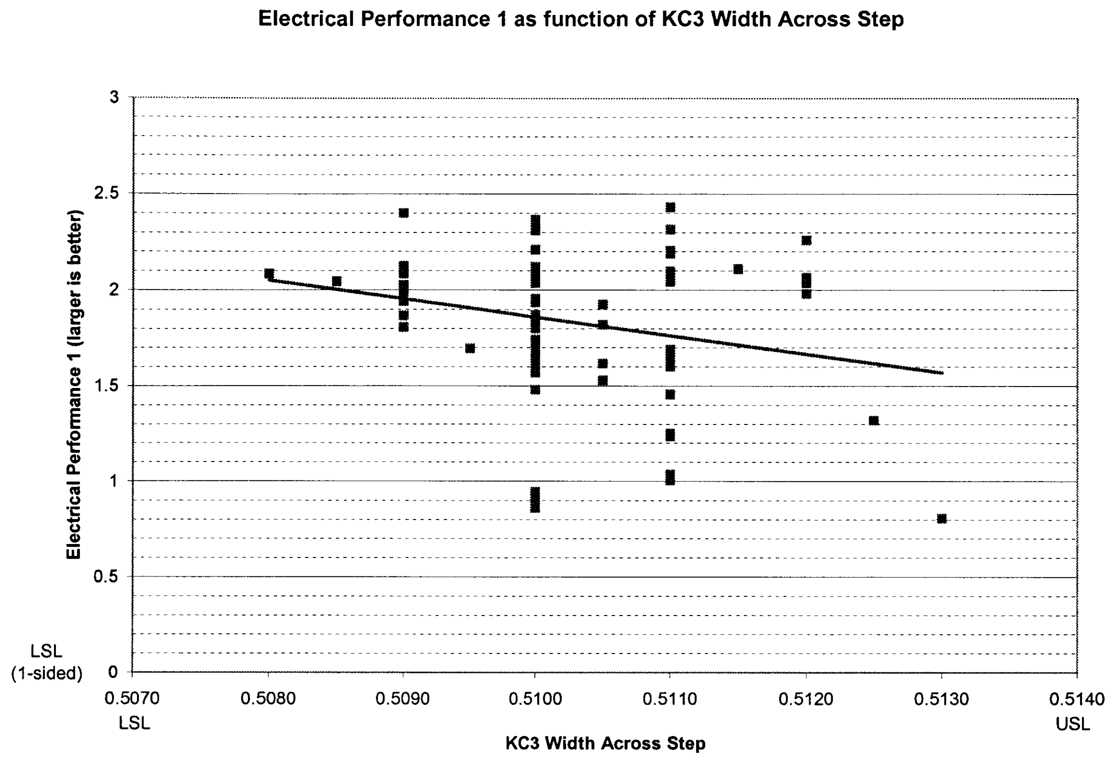

Figure 5: Scatter Plot and Regression Line for KC3 Width Across Step

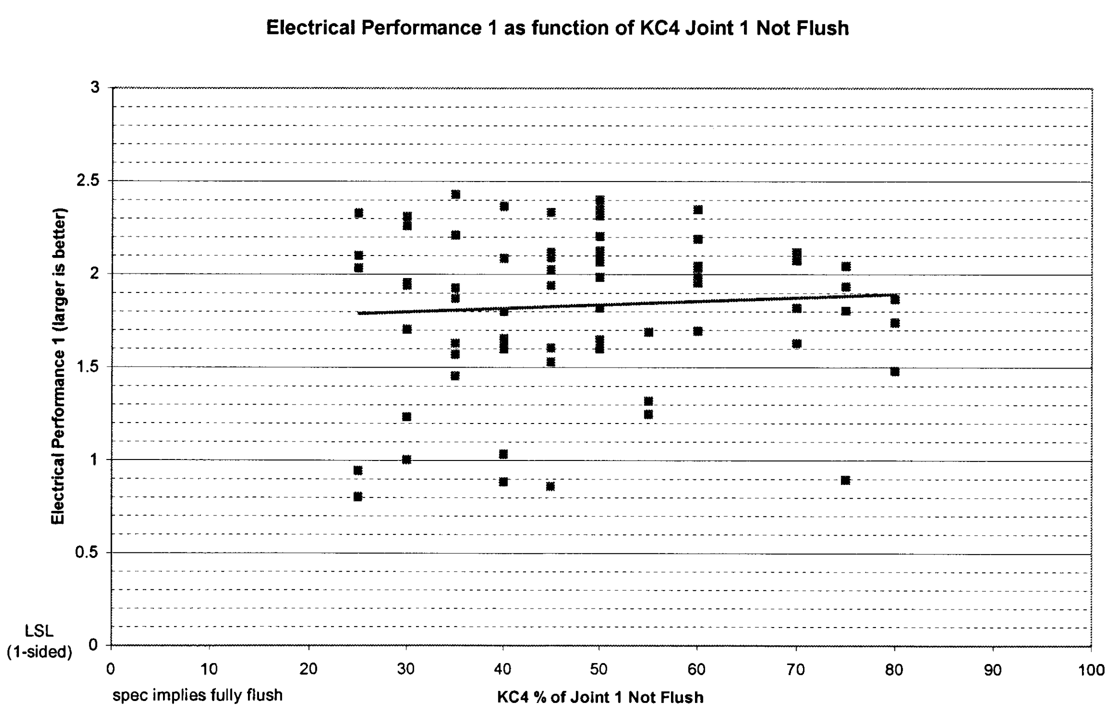

Figure 6: Scatter Plot and Regression Line for KC4 Percent of Joint 1 Not Flush

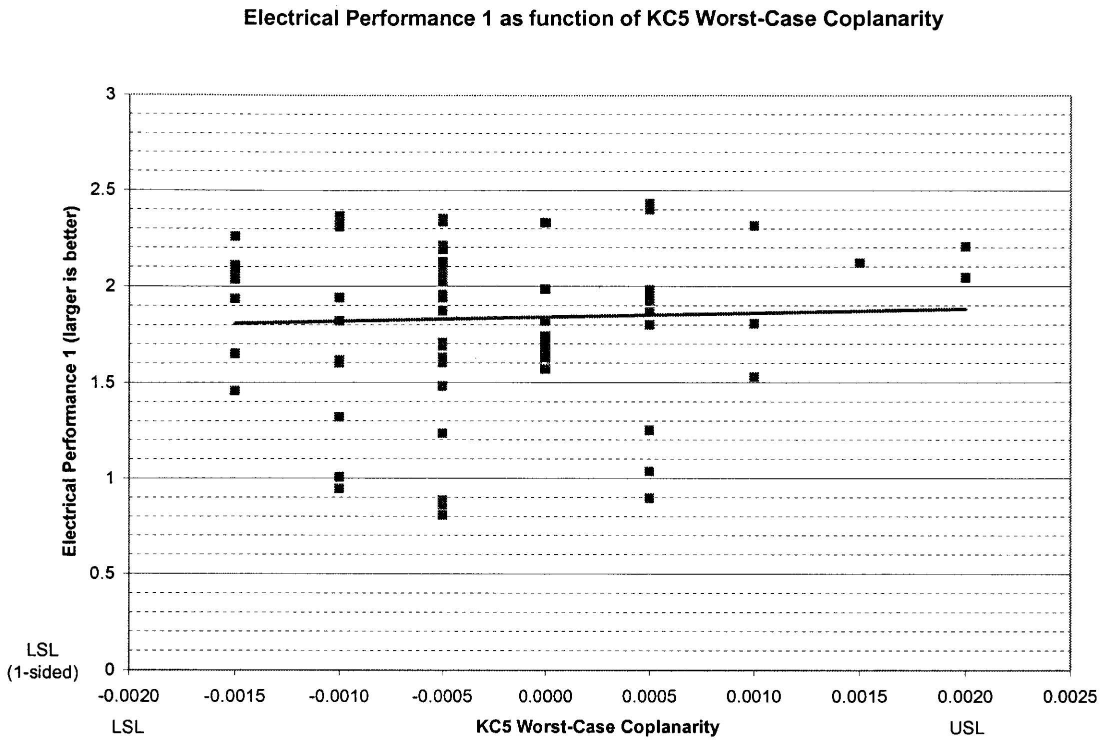

Figure 7: Scatter Plot and Regression Line for KC5 Worst-Case Coplanarity

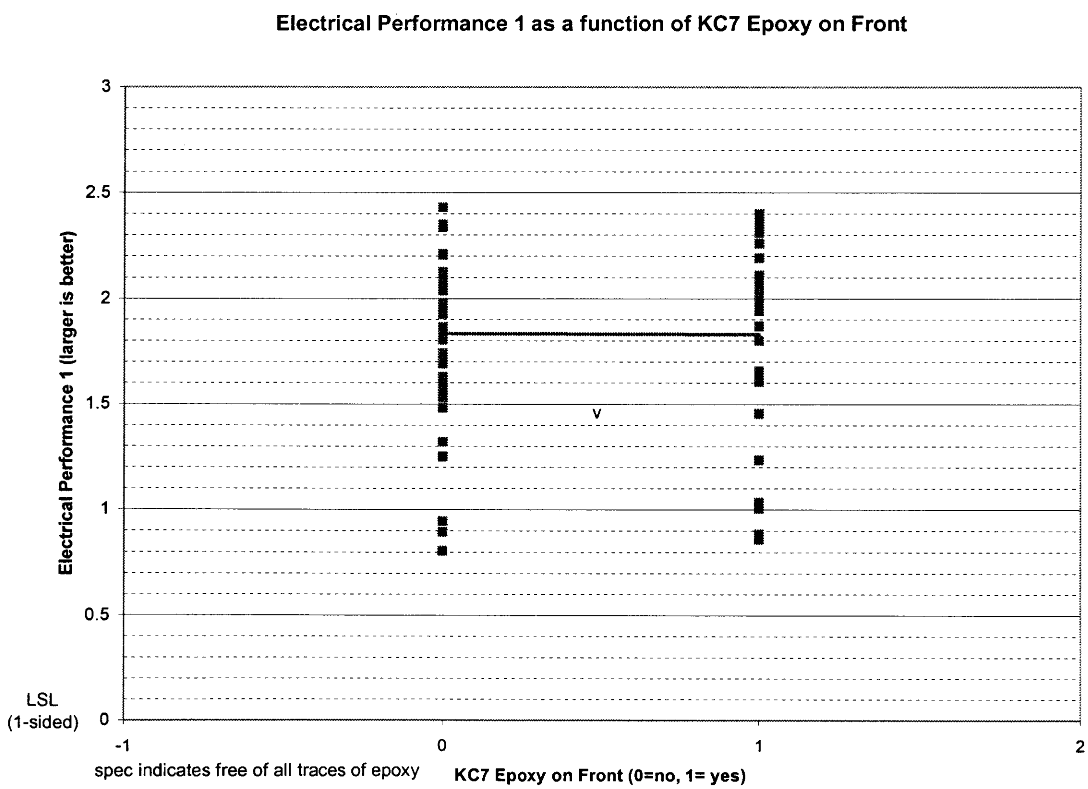

Figure 8: Scatter Plot and Regression Line for KC7 Epoxy on Front

For the five parameters contributing to Electrical Performance 1, the first observation is that with the given dataset, electrical performance for all units was within the single-sided performance specifications (LSL=0).

Of all these parameters, KC3 in Figure 5 shows the strongest indication of impact on performance over the range of parameter values, as shown by the steepest sloped regression line. However, the plot shows that the fit is still rather weak, with slope strongly dependent on a few points near the outer limits of the dataset. While these few outer points indicate the possibility of a performance impact, the full range of performance variation is strongly evident in the middle region of the dataset. Simply tightening up the variation in KC3 towards the middle of the spec range would likely do little to improve expected performance.

The other four features exhibit little or no correlation to performance, with linear regression lines virtually flat. This lack of correlation was surprising, and indicates that these features are not as key to performance as was originally thought.

KC2 in Figure 4 shows a roughly uniform distribution of performance across all observed widths, with the range biased toward the upper end of the tolerance band. This is an example of a process that is in control and meeting specs. This feature cannot be justified as key based on this data.

KC4 in Figure 6 also shows no significant correlation to performance. Of interest in this case is that the specification calls for the joint to be fully flush. None of the samples met the specification, yet there appears to be little impact in performance over the existing range of observed joint flushness. This indicates an opportunity for cost avoidance. Meeting the existing spec would require additional cost in the implementation of process controls and inspection, while there would appear to be little projected performance benefit. The existing process variation meets performance requirements, providing evidence to remove the spec on joint flushness.

For KC5 a policy of 100% inspection had been implemented to meet the drawing spec for coplanarity, with a resulting scrap or rework rate of approximately 5%. However, as with the other parameters, Figure 7 shows there is little correlation between this feature and performance. This indicates a potential to relax the existing spec, with cost savings due to reduced or eliminated inspection, scrap and rework. As this dataset does not include values outside the spec range, a designed experiment with properly selected values outside the existing spec range would provide the definitive results required to justify such a decision.

KC7 in Figure 8 indicates another opportunity for cost avoidance. Approximately half of the samples did not meet spec, showing some significant degree of epoxy contamination on the front face of the part. However, given existing process variation, there appears to be almost no difference in performance for those parts that were contaminated. Rather than implement either process controls to prevent the contamination or rework procedures to remove it, the data indicates that the spec could be relaxed to allow for existing levels of contamination with no resulting impact on performance.

4.3.2 KCs Impacting Performance Measure 2

Results for Electrical Performance 2 are presented here, with respect to the following contributing parameters: KC6, KC8, KC9, KC10, KC11, and KC12. Scatter plots are shown in Figure 9 through Figure 14, followed by observations.

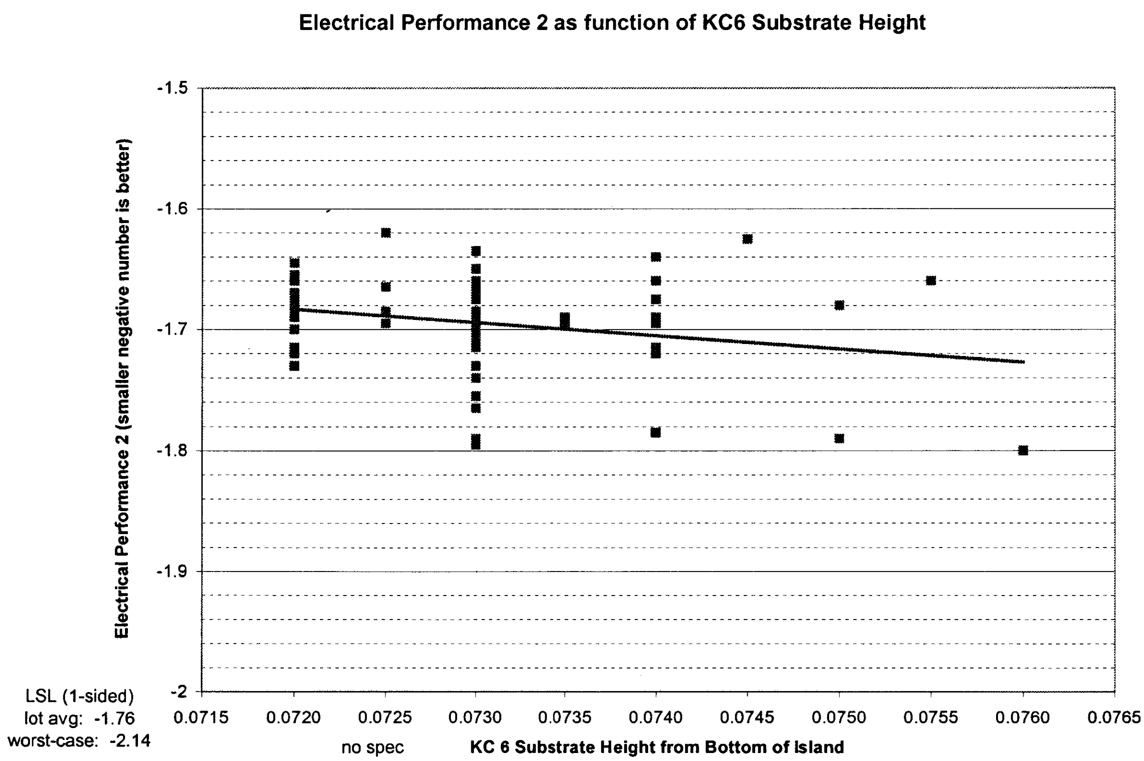

Figure 9: Scatter Plot and Regression Line for KC6 Substrate Height

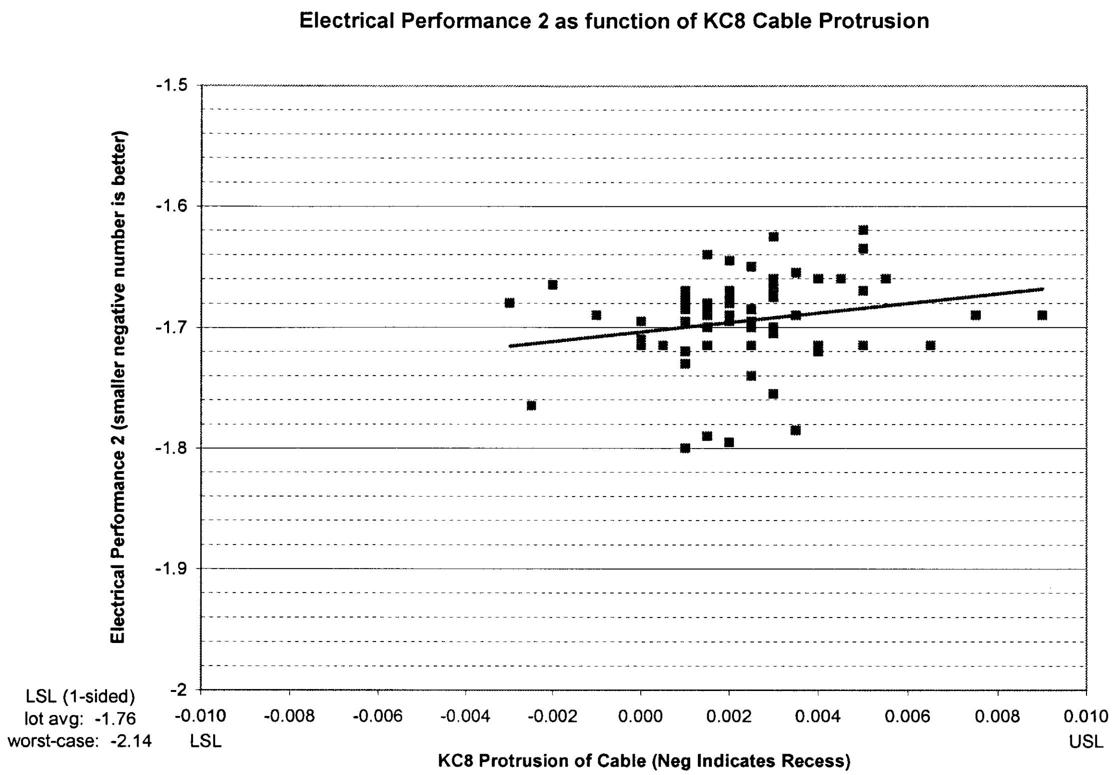

Figure 10: Scatter Plot and Regression Line for KC8 Cable Protrusion

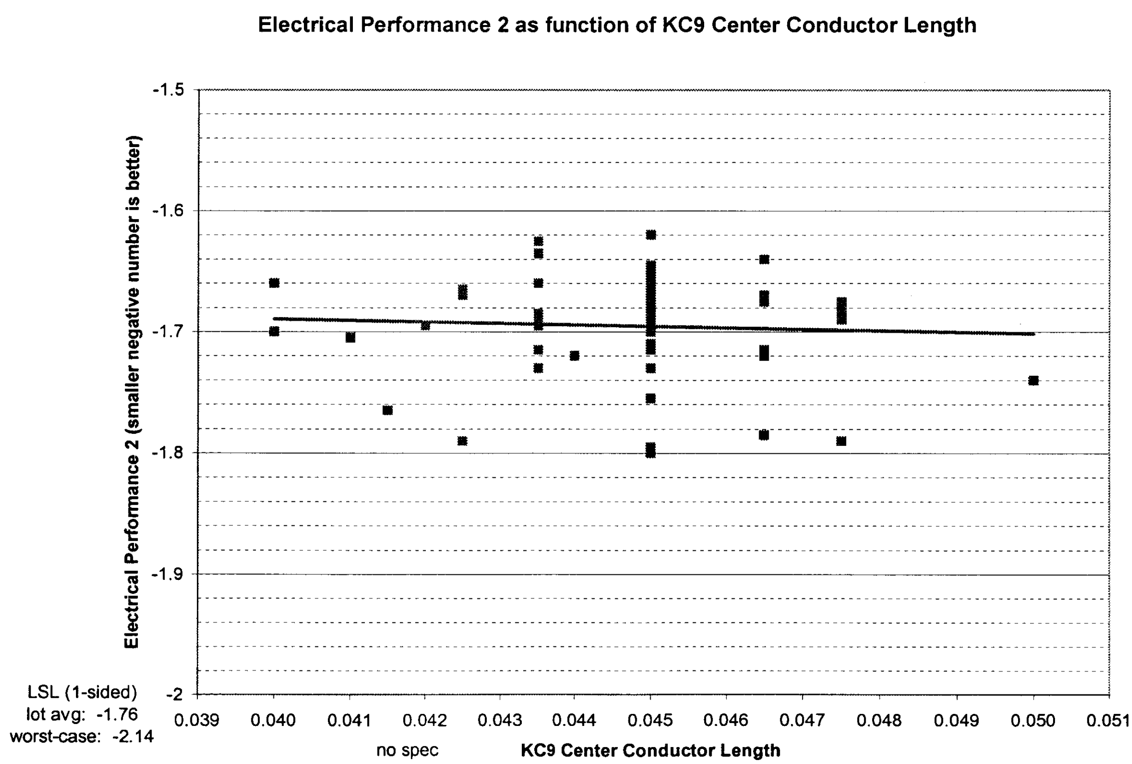

Figure 11: Scatter Plot and Regression Line for KC9 Center Conductor Length

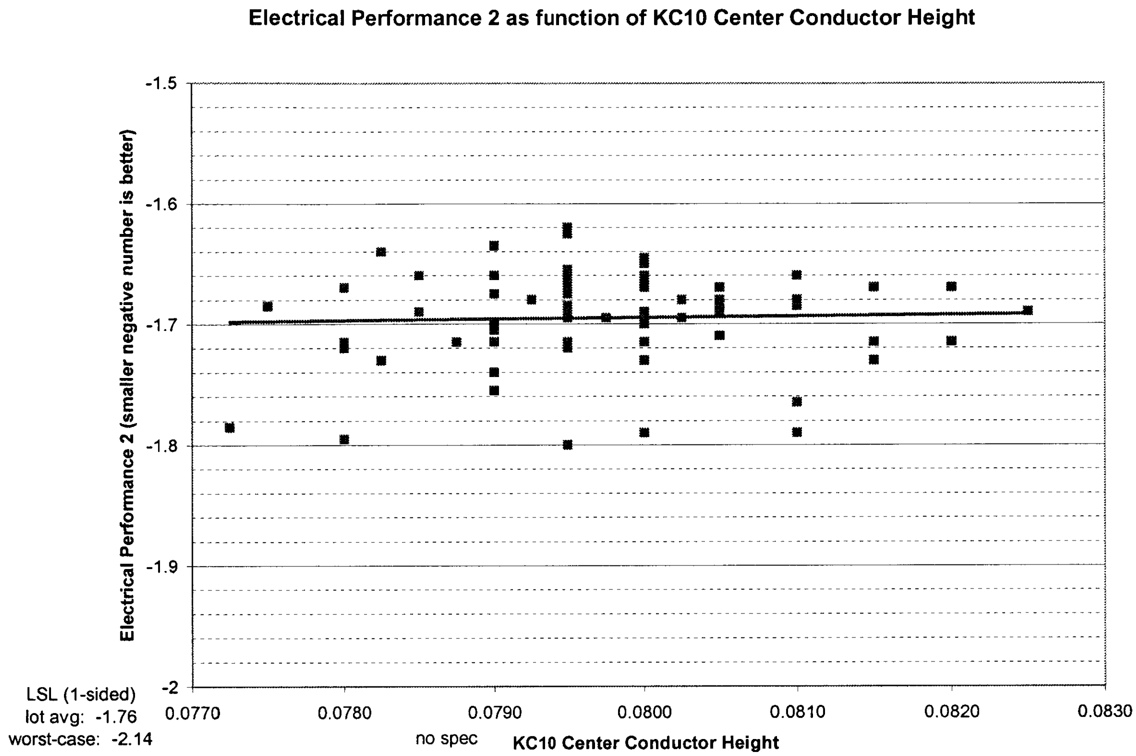

Figure 12: Scatter Plot and Regression Line for KC10 Center Conductor Height

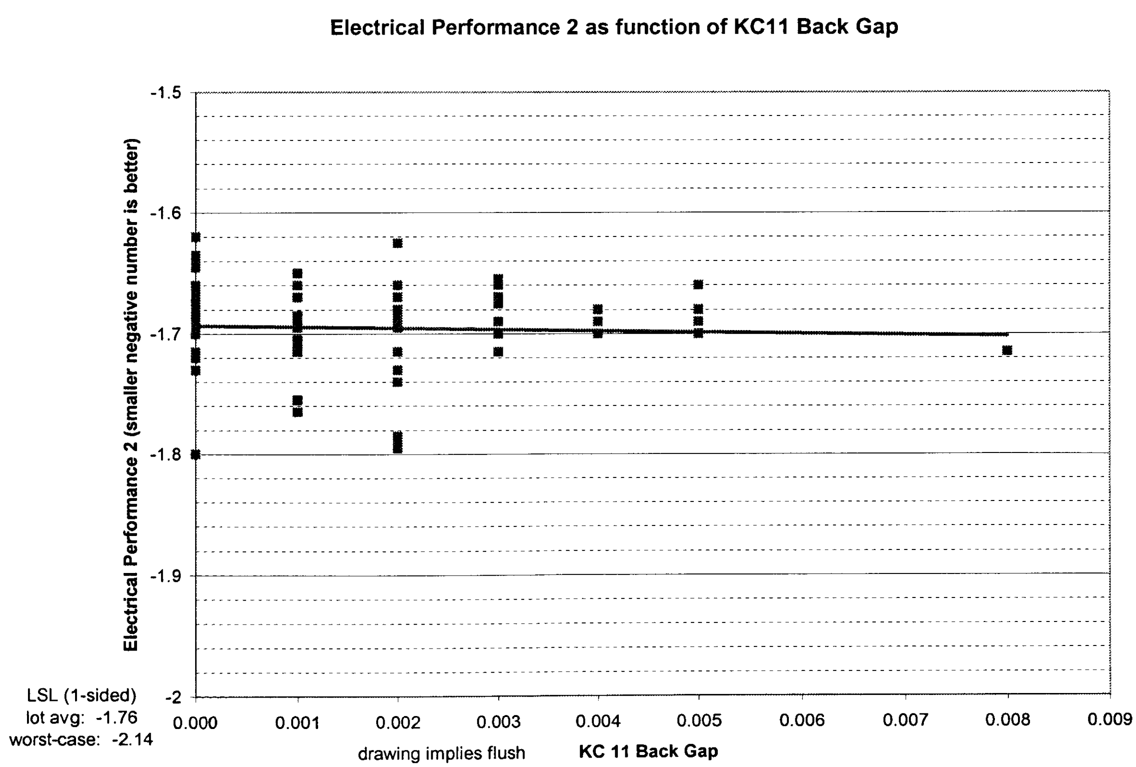

Figure 13: Scatter Plot and Regression Line for KC11 Back Gap

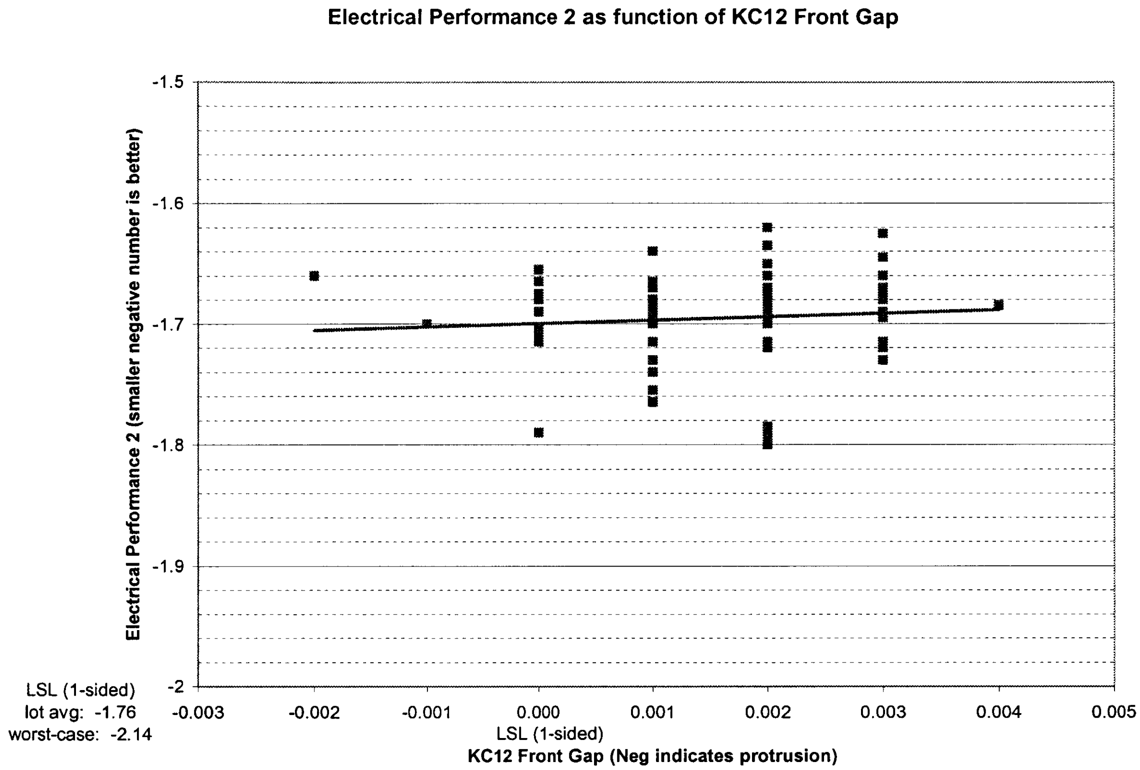

Figure 14: Scatter Plot and Regression Line for KC12 Front Gap

For the six parameters contributing to Electrical Performance 2, the first observation is that with the given dataset, electrical performance for all units was within the single-sided performance specifications (LSL = -2.14 worst case and -1.76 on a lot average basis).

Of these six parameters, KC6 in Figure 9 and KC8 in Figure 10 show the strongest relative correlation to performance. However, these both exhibit the same issue as KC3 from the previous section, that is, the regression slope is influenced by a few points near the ends of the range.

There is currently no specification on KC6, and all samples met the performance requirements. If there were a need for greater performance, it may be worth investigating the use of process controls to restrict variation in substrate height to the low end of the dataset where performance is both improved and experiences less variation (see Figure 9). The performance improvements would need to justify the cost of such controls. KC8 in Figure 10 tells a similar story, where there may be a potential for slight performance gains through the use of process controls that would maintain cable protrusion near the upper spec limit.

For KC9 in Figure 11 and KC10 in Figure 12, there is no significant correlation of these parameters to performance. No specifications are given for these features, and reducing variation in center conductor length and height around the center of their respective datasets is not anticipated to improve performance, as most of the variation in performance occurs in these middle regions.

KC11 in Figure 13 and KC12 in Figure 14 also show no significant correlation of parameters to performance. The drawing implies a flushness spec for KC11, that is zero back gap, a condition that the majority of assemblies did not meet. For KC12 the spec indicates that protrusion is not allowed, that is, front gap must be positive, a condition that a few of the assemblies did not meet. However, in both cases, these conditions outside of specs did not appear to have a negative impact on measured performance. This data indicates that the existing processes are capable of meeting the performance requirements and that further investment in process controls to insure compliance with specs would not result in increased performance.

4.3.3 Multivariate Analysis and Interactions

While individual features show little or no correlation to performance, it is possible that performance is dependent on interactions of features. To explore these interactions, a multivariate analysis was performed using JMP, a statistical analysis software package[27]. This analysis was performed separately for each of the two electrical performance measures.

Figure 15 shows results for the first measure of electrical performance (P1) and its associated parameters (KC2, KC3, KC4, KC5, and KC7). Likewise Figure 16 shows results for the second measure of electrical performance (P2) and its associated parameters (KC6, KC8, KC9, KC10, KC11, and KC12). Each of these figures has two elements. The first is a correlation matrix that shows correlations between all parameters and the performance measure. The second is a matrix of two-dimensional scatterplots showing relationships among all parameters and the performance measure. Density ellipses in red are set to enclose 95% of data points. A third dimension has been added to these plots through the use of color. Each marker in the plot is colored according to its performance measure, across the spectrum of red to violet. This spectrum can most easily been seen in

[27] *JMP In* Version 4.0, SAS Institute Inc., website http://www.sas.com.

the plots for the performance measures (P1 and P2) where for these graphs the added color dimension is redundant.

Multivariate

Correlations

	KC2	KC3	KC4	KC5	KC7	P1
KC2	1.0000	0.2723	-0.1735	-0.1367	0.0540	0.0173
KC3	0.2723	1.0000	-0.1479	-0.0789	0.0687	-0.2195
KC4	-0.1735	-0.1479	1.0000	0.2976	-0.4526	0.0696
KC5	-0.1367	-0.0789	0.2976	1.0000	-0.1868	0.0404
KC7	0.0540	0.0687	-0.4526	-0.1868	1.0000	-0.0048
P1	0.0173	-0.2195	0.0696	0.0404	-0.0048	1.0000

Scatterplot Matrix

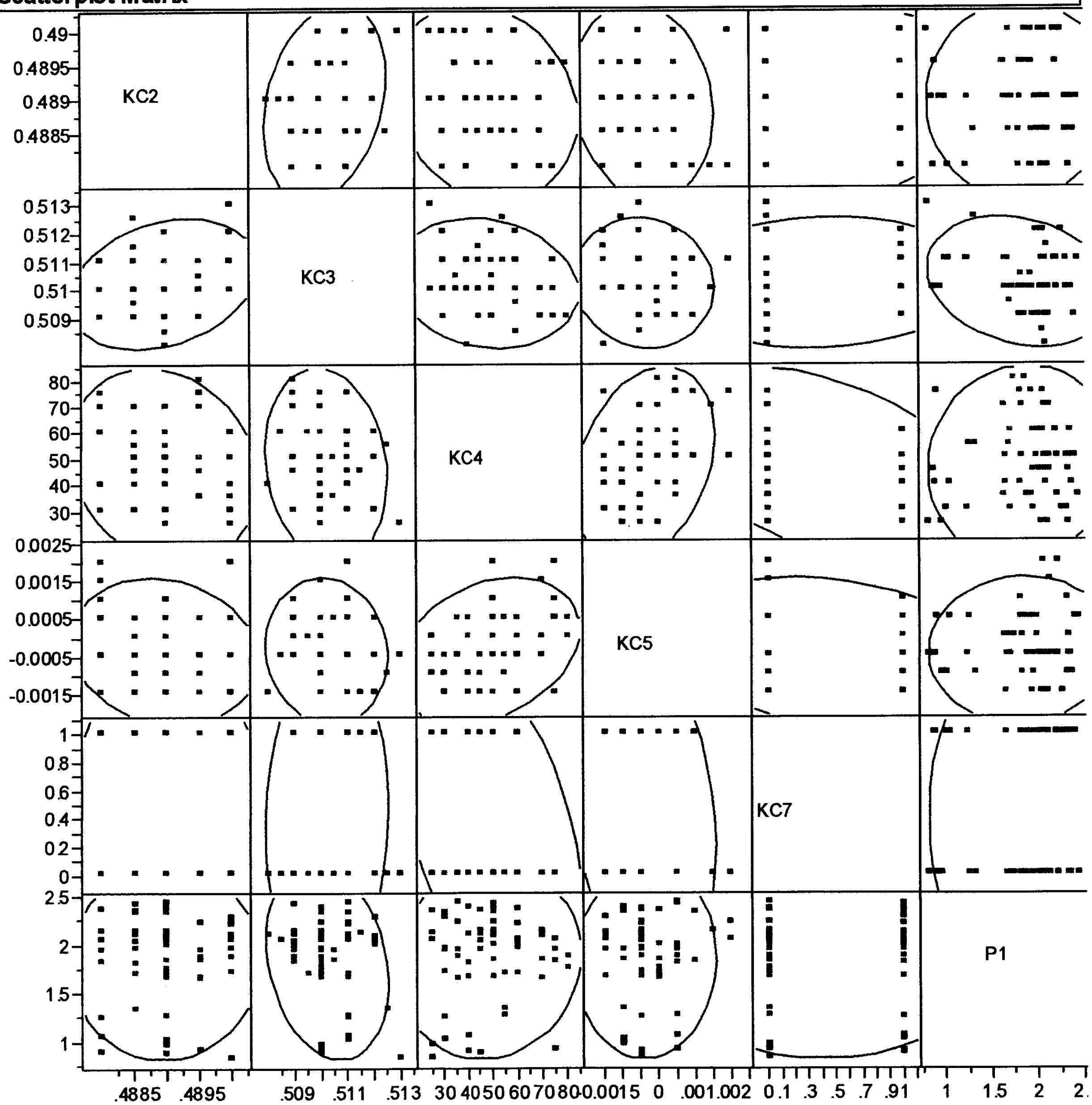

Figure 15: Multivariate Analysis for all KCs contributing to Electrical Performance 1: Correlation Table and Scatter Plot Matrix

Multivariate

Correlations

	KC6	KC8	KC9	KC10	KC11	KC12	P2
KC6	1.0000	-0.0224	-0.0503	0.2298	-0.0489	0.1237	-0.2428
KC8	-0.0224	1.0000	0.0552	-0.0293	0.0461	0.1267	0.2044
KC9	-0.0503	0.0552	1.0000	-0.1086	-0.1519	0.1410	-0.0524
KC10	0.2298	-0.0293	-0.1086	1.0000	-0.1440	0.0919	0.0329
KC11	-0.0489	0.0461	-0.1519	-0.1440	1.0000	-0.4737	-0.0446
KC12	0.1237	0.1267	0.1410	0.0919	-0.4737	1.0000	0.0860
P2	-0.2428	0.2044	-0.0524	0.0329	-0.0446	0.0860	1.0000

Scatterplot Matrix

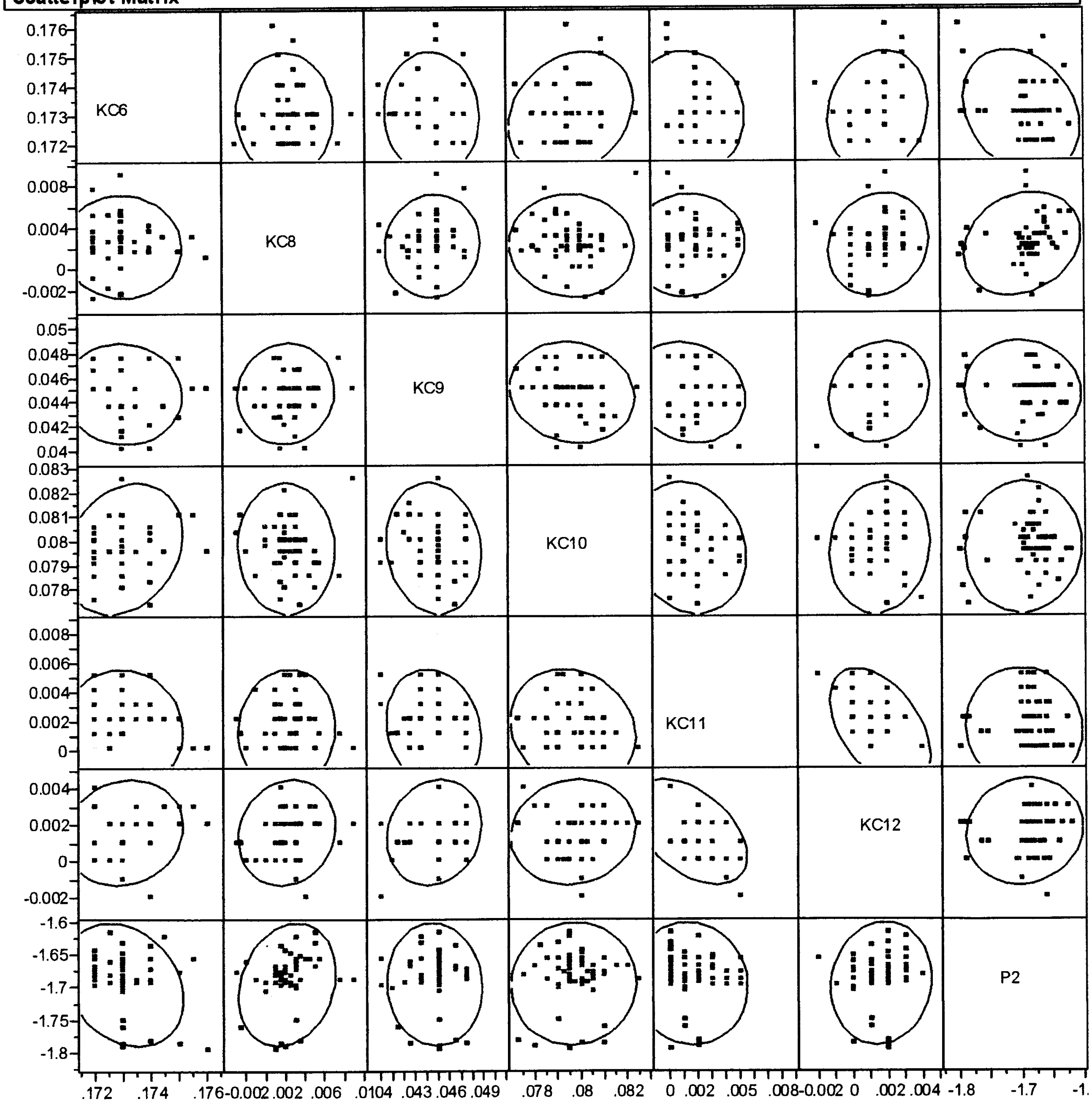

Figure 16: Multivariate Analysis for all KCs contributing to Electrical Performance 2: Correlation Table and Scatter Plot Matrix

Figure 15 and Figure 16 were examined for evidence that two-way interactions of parameters impact the respective performance measures. A strong interaction would be evident by distributions of color patterns in plots between two of the KC*x* parameters.

For example, in Figure 15, the better performing units correspond to higher values of P1, with colors near the violet end of the spectrum (mostly blues) and poorer performing units have lower values of P1, with colors near the red end of the spectrum. No clear patterns were seen, with both red and violet/blue markers appearing randomly diffused in the two-way parameter plots. In Figure 16, the better performing units correspond to smaller negative values of P2, again with colors near the violet end of the spectrum and poorer performing units with larger negative values of P2, with colors near the red end of the spectrum. Again, there appears to be no clear evidence of spatial separation between the red and violet/blue markers.

4.4 Summary of Data Analysis

In summary, correlations of these features to their respective performance measures were weak. Of the eleven features measured, only three showed evidence of correlation (KC3, KC6, and KC8), and the significance of those correlations is questionable in all three cases, given that just a few outer points dominated the slope of the regression.

There was not strong evidence to confirm these characteristics as key with respect to performance measures. There are a number of possible conclusions as to why this is the case. One possibility is that KCs were not properly identified. This means that observed variation in performance may be due to features that were either never identified or eliminated from consideration when the list of candidate KCs was reduced. This would indicate the need for improved methods to identify KCs. In such an assembly where there are relatively complex relationships between parameters and performance, better analytical tools may be needed. If it is found that software models cannot accurately describe these relationships, then Design of Experiments can be helpful. The choice of performance measures is also a factor in identifying KCs. It is sometimes a challenge to select performance measures that both properly reflect customer needs and can be accurately measured with reasonable effort and available equipment. With multiple electrical performance parameters that characterize microwave assemblies, there are choices of how required performance is defined (ie. which performance measures are important, how many different measures are needed, what are reasonable tolerances, how should these be measured, etc.).

An alternative hypothesis for why the data analysis did not confirm the selected parameters as KCs is that is that the design is highly coupled, so that variations in many parameters interact to affect performance. In this case the performance of this design is not dominated by variation in a few features that directly correlate to performance, but rather is determined by variations in a large number of features, with complex interactions. Electrical design engineers associated with the project indicated that this is typical of electro-mechanical assemblies designed to operate at microwave frequencies. Simple two-way interactions were explored in the scatterplot matrices. While these interactions did not show a strong impact on performance, it is possible that other interactions are important. These could include interactions with parameters not measured and/or higher order interactions. If this is the case then more sophisticated analysis methods are needed to understand these interactions and their impact on performance.

There are other possibilities for why the parameters examined did not show an anticipated level of impact on performance. It may be that the design is more robust than expected, that is, variation in parameters would have little effect on performance. If this is true, it is important to understand the properties of the design that result in robustness. It is also possible that the parameters studied do have a significant impact on performance, but that tolerances have been tightly constrained to levels that result in little or no performance variation. If this is true, then understanding the relationship between these parameters and performance measures will likely create opportunities for cost savings by relaxing specifications to levels that acceptable performance specifications will allow.

It appears that measurement error may be a significant source of variation in these measurements. Analysis of expected measurement error would be helpful to quantify the sources and magnitude of variation due to measurement in electrical performance measures as well as KCs. This can be accomplished using a Gage R&R (repeatability and reproducibility) study, a statistical tool that measures magnitude and source of variation in measurements. Error bars, both horizontal and vertical, could then bound each point on the scatterplots, visually indicating the relative importance of measurement errors in overall variation. The absence of such information weakens the case for establishing a correlation between variation in KCs and electrical performance.

Perhaps the most significant of these observations is the potential for cost savings. This occurs where variation in a parameter does not appear to impact performance, yet parts are being inspected, then scrapped or reworked due to not meeting specifications. With designed experiments using parameter levels outside of the current spec range it may be possible to confirm that specifications can be relaxed and inspection, scrap and rework can be reduced or eliminated.

Section 5: KCs and the Design Process: An Example

5.0 Section Overview

A benefit of KC identification is that it helps to focus the concurrent engineering of product and process on those features of the design that are most important. This became clear in the process of identifying KCs for Subassembly A. This section follows the development of a process for one of the critical joints on Subassembly A. It illustrates how identifying and questioning the KC for this joint led to a more robust design.

5.1 Joint 2

Figure 17 diagrams the cross-section of a portion of Subassembly A, where "Joint 2" is shown as an electrical connection between the center conductor of a cable and the plated wall of a hole. The KC identified for this joint is the "Void Depth." Finite element analysis simulation results were confirmed with laboratory experiments to show that variation in the depth of the void has a significant impact on the RF electrical performance of the subassembly.

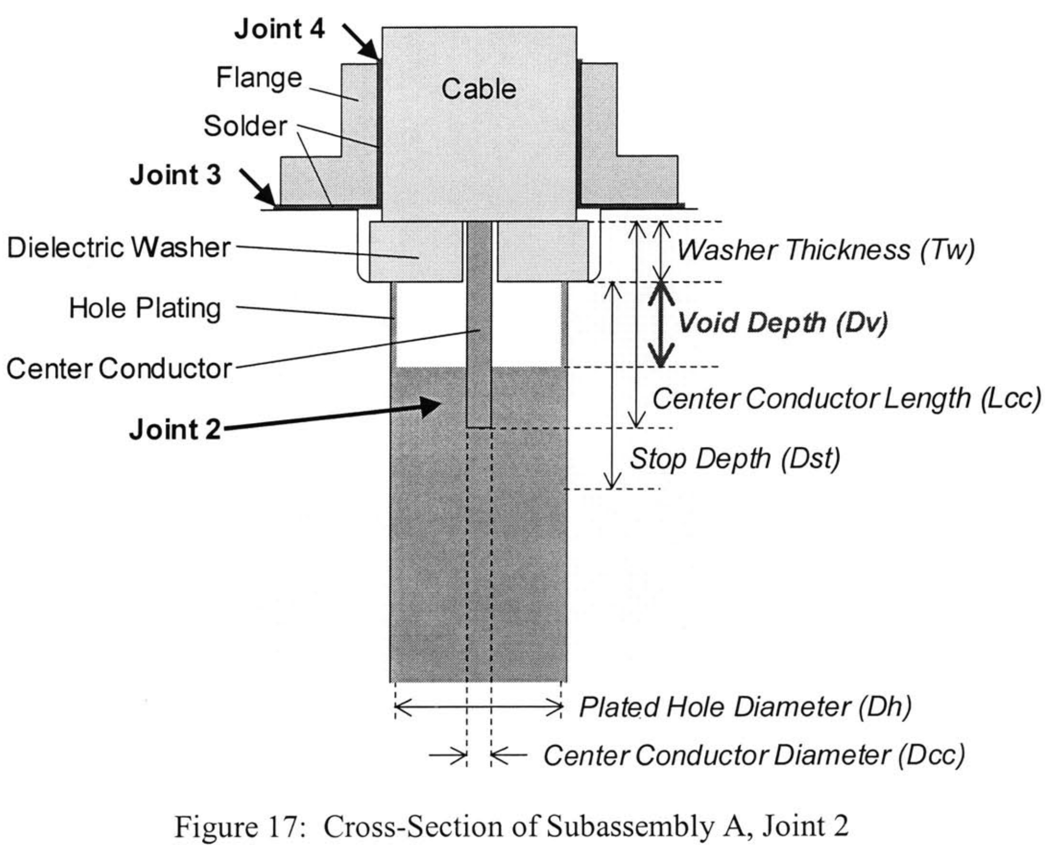

Figure 17: Cross-Section of Subassembly A, Joint 2

5.2 A Proposed Solder Preform Process

A number of alternative methods were proposed to create Joint 2, including the use of either electrically conductive epoxy or solder. One promising method is based on the use of solder "preforms." These are now available in a wide variety of form factors and solder types, and can be custom ordered to precise dimensions[28]. This section will present a simplified version of a Joint 2 design using a solder preform. The intent is not to present a comprehensive description of the many factors involved in the design, but to present those that demonstrate the role of KCs in this development process.

The method proposes inserting a solder stop, a high-temperature rubber plug, into the plated hole, followed by a cylindrical solder perform as shown in Figure 18.

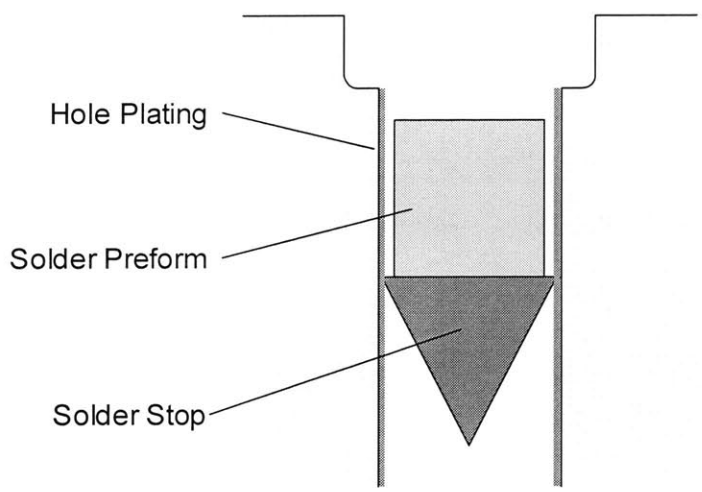

Figure 18: Solder Stop and Cylindrical Solder Preform Inserted in Plated Hole

The unit is then placed in a special-purpose fixture and heated in an oven, while the solder stop prevents the solder from flowing down the sides of the hole. The fixture holds the cable aligned and allows it to drop into the molten solder, completing the joint as shown in Figure 19. The flange shown in the finished joint of Figure 17 can then be slipped over the cable and manually soldered to give the joint mechanical strength and create the required electrical connection between the cable jacket and outside of the unit.

[28] Indium Corporation of America, *A Quick Guide to Solder Preforms*. Available from http://www.indium.com.

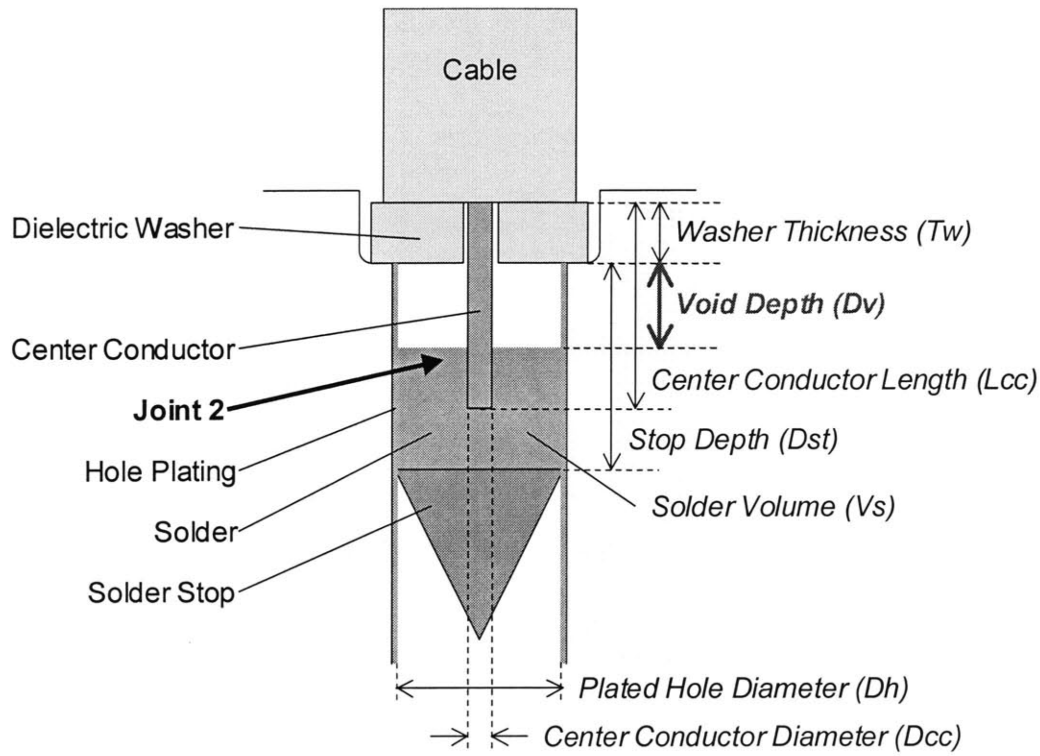

Figure 19: Joint 2 after Solder Reflow

A traditional approach then takes this proposed design and selects targets for the basic parameters of the joint, choosing tolerances for each to limit the impact of variation on product performance. In this case variation in the parameter identified as Void Depth was determined to have the greatest impact on product performance. We can recognize that variation in the resulting Void Depth will depend on a stackup of variation in a number of physical parameters: Stop Depth, Solder Volume, Plated Hole Diameter (itself a function of variations in hole diameter and plating thickness), Center Conductor Diameter, Center Conductor Length, and Washer Thickness.

From a worst-case perspective, it is possible to identify the disallowed conditions shown in Figure 20, then calculate worst-case specifications for all those parameters subject to variation. Given random variation in these parameters, a worst-case analysis results in specifications that are unnecessarily tight. A better approach might be the use of statistical tolerancing techniques, as described by Whitney[29]. However, instead of

[29] D.E. Whitney, *Mechanical Assemblies: Their Design, Manufacture, and Role in Product Development*, to be published by Oxford University Press, 2003, Chapter 5: Dimensioning and Tolerancing Parts and Assemblies.

proceeding on this path, let us back up and look at this design from the perspective of the KC.

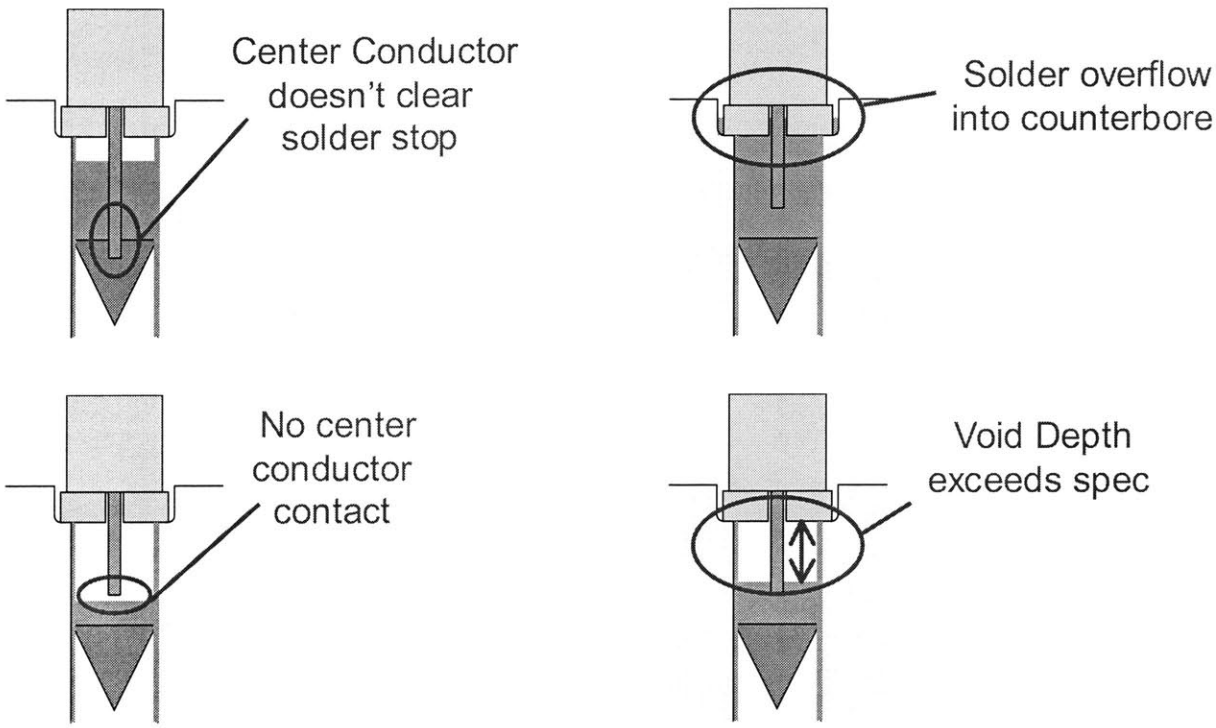

Figure 20: Defective Conditions for Joint 2

5.3 KCs Give Perspective on Design Alternatives

At this point, we step back from the design to take a closer look at the KC. Why is Void Depth a KC? Tolerancing studies were done on the proposed design and variation in Void Depth was found to impact RF electrical performance. In this case the metric directly related to customer requirements is electrical performance. In terms of a very simple KC flowdown, electrical performance is considered the primary KC and Void Depth is considered a derived KC. Why is this distinction important? Primary KCs *must* be met because they are directly linked to customer requirements. However, derived KCs are artifacts of the chosen product and/or process design. For any given design it is expected that most of the KCs will be derived.

It is correct that Void Depth is critical for *this* particular design, but might there be other designs where electrical performance is not dependent on Void Depth, or where Void

Depth is not subject to stackup in variation of other parameters? Is there a design that will allow us to more directly control the variation in KCs around their target values? Or is there a design that is so different that it doesn't have a void and thus has no void depth? A robust design can be achieved if the variation inherent in the associated part, process, and assembly parameters has little effect on performance requirements.

This type of questioning led to the suggestion that the process for creating this joint literally be turned upside-down. Starting with a "not-to-exceed" spec for void depth, it was determined that ideally there would be no void whatsoever. Targeting a zero-void joint in an upside-down configuration led to the proposed joint design shown in Figure 21.

An added feature of this design is the flange soldered to the centered conductor. This achieves a thinner solder joint to minimize the stress associated with coefficient of thermal expansion mismatches in the solder and walls of the plated hole. A minimum joint length is needed to insure a good joint, but a joint that is too long was shown to result in undesirable stresses. The taper on the flange makes the joint length robust to variation in other parameters such as solder volume or hole diameter.

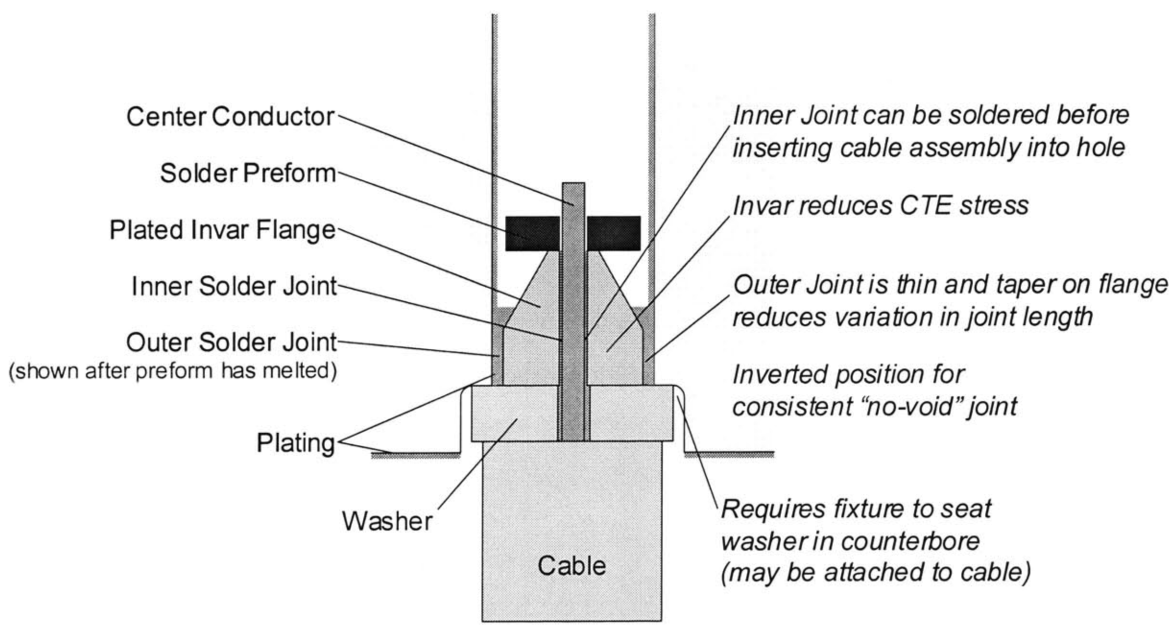

Figure 21: An Alternative Design for Joint 2

At the time this design was suggested, initial production was already underway with a process based on a conductive epoxy. Initial results of the epoxy process showed potential promise. This design was held in reserve pending further production experience with the epoxy process. No new derived KCs were anticipated in this alternative design.

In summary, this simplified description provides an example of how KCs can be used to focus the design process on those parameters that have the greatest impact on performance, resulting in more robust designs. Because KCs cut across product and process and supply chain boundaries, they act as a communication aid to organizations that are trying to improve concurrent engineering design in order to improve the transition from design to production. Identifying and communicating KCs establishes common goals for all design and manufacturing personnel.

Looking at causes of inaccuracies in manufacturing process simulations led us to question expected first-pass yield inputs to the model. This in turn led to identification of Key Characteristics (KCs) as a way to focus on features with the greatest impact on customer performance requirements. Having addressed KCs as the root of this predictability chain, we now examine the next step: predicting first-pass yields for manufacturing process modeling.

Section 6: Predicting First-Pass Yields for Manufacturing Process Modeling

6.0 Section Overview

Radar Subassemblies are precise mechanical subassemblies that go through many specialized production process steps. As part of manufacturing system design, inspection and test procedures are established at various stages in the production process. Each inspection point has an associated first-pass yield, with rejects resulting in either scrap or rework.

This section will discuss what Raytheon is currently doing to predict first-pass yields, then look at an underlying mathematical framework and method to apply it to Subassembly A in a simple spreadsheet model. We will then return to where this project started, with a brief description of use of manufacturing process modeling at Raytheon.

6.1 Process Capability Analysis Toolset (PCAT)

Raytheon has significant experience in predicting yields based on process capability. They have developed a custom software tool, the Process Capability Analysis Toolset (PCAT), for predicting first-pass yield, cost, and cycle time early in the product design process. Its purpose is to assist in quantifying the "impact of key design features and characteristics on manufacturing process, enabling tradeoffs early in the design process"[30]. PCAT uses a database of process capability models based on historical data and expert knowledge validated against actual production data. A graphical user interface allows a designer to input the associated process and parameters for a given design. The software then queries the database for Defects Per Unit (DPU) estimates of each process and combines these to give a resulting DPU and associated first-pass yield prediction for the design.

At Raytheon's Andover facility, PCAT is presently used extensively in areas such as Circuit Card Assembly and Metal Fabrication. However, at the time this project began, the appropriate DPU data did not yet exist for the processes required for Subassembly A and similar electro-mechanical subassemblies. A project has been initiated to develop these models and make them available to evaluate future radar subassembly designs.

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[30] *PCAT Process Capability Analysis Toolset*, internal Raytheon Company training materials

In the absence of a PCAT model for Radar Subassembly A, a simple spreadsheet model was created that uses a DPU estimation method similar to that used by PCAT. A brief summary of the mathematical basis for DPU estimation of first-pass yield is presented, followed by a description of the spreadsheet model implemented for Subassembly A.

6.2 Mathematical Basis for First-Pass Yield Estimates

This section presents a brief summary of the mathematical basis for using DPU estimates to predict First-Pass Yield for assemblies. Portions of the brief summary presented here draw heavily on Motorola Six Sigma training materials[31]. We start with a few definitions:

- *First-Pass Yield* for a given test or inspection step is the ratio of units that pass the first time over total number of units tested for the first time.
- *Defect* is defined as a fault in a part, subassembly, or process that causes a unit to fail test.
- *Defects Per Unit (DPU)* is the ratio of defects found at all acceptance points over total number of units produced.

Defects are typically distributed either uniformly or randomly in a unit. Using the example of an electronic circuit card assembly, if a wrong part is placed in a parts bin, every circuit board will contain the wrong part in the same location, resulting in a uniformly distributed defect. However, mixed parts in the same bin would create randomly distributed defects, where the probability of a defect is dependent on the proportion of wrong parts in the bin. Uniform defects are easiest to locate, fix, and prevent, while randomly distributed defects are usually more challenging. For this analysis, first-pass yields are estimated based on randomly distributed defects.

The Poisson distribution is useful in finding a relatively simple formula for estimating first-pass yield given the assumption of randomly distributed defects. In a Poisson distribution, an unknown number of items are scattered over some type of "region". With this region divided into extremely small increments of size ε, a distribution is considered Poisson with parameter λ if the following apply:

[31] *Design for Manufacturability,* Motorola Six Sigma Training Course ENG 123, 1990.

- the probability that exactly one item falls in a given increment of size ε is $\lambda\varepsilon$
- the probability that no items fall in such an increment is $(1- \lambda\varepsilon)$
- increments are independent as to whether they contain items

The parameter lambda can be interpreted as the average number of items in a unit interval of the region. The Poisson formula then gives the probability that x items will occur during a given interval T, where $\mu = \lambda T$ is the average number of items in interval T, and e is the mathematical constant (≈ 2.718):

$$P\{x\} = (\mu^x \cdot e^{-\mu}) / x!$$

Often the Poisson distribution is applied to events occurring in time, but in this case it is applied to defects occurring in the possible "defect space" of an assembly unit, that is, the space comprising possible opportunities for creating defects in the assembly. While a proof is not presented here, it has been demonstrated that these randomly distributed defects can be modeled as a Poisson distribution. In the Poisson formula, we can let x = number of defects, and μ = expected defects per unit (DPU), such that for a given unit the probability of zero defects is

$$P\{0\} = (DPU^0 \cdot e^{-DPU}) / 0! = e^{-DPU}$$

Recognizing that probability of zero defects is First-Pass Yield, we have

$$FPY = e^{-DPU}$$

In the case of radar subassemblies there are multiple opportunities for defects in parts and assembly processes. Each of these (A, B, ..., N) results in a First-Pass Yield that can be found from an associated DPU:

$$FPY_A = e^{-DPU_A}, FPY_B = e^{-DPU_B}, \ldots, FPY_N = e^{-DPU_N})$$

The *Rolled First-Pass Yield*, or probability of a unit going through the entire process without defects can be found by the joint probabilities:

$$\begin{aligned}
&\text{Rolled First-Pass Yield} = P\{0 \text{ defects for all process steps}\} \\
&= P\{0 \text{ defects at A}\} \cdot P\{0 \text{ defects at B}\} \cdot \ldots \cdot P\{0 \text{ defects at N}\} \\
&= e^{-DPU_A} \cdot e^{-DPU_B} \cdot \ldots \cdot e^{-DPU_N} \\
&= e^{-(DPU_A + DPU_B + \ldots + DPU_N)}
\end{aligned}$$

This result doesn't depend on process flow, only on the DPUs. However, the result assumes independence of opportunities for defect. That is, the existence of one defect does not change the probability that another defect will occur. Because this is not always strictly true in practice, this result can be expressed as an approximation rather than an exact result.

In conclusion, we end up with a very simple way of estimating first-pass yield for an assembly: Identify the opportunities for defects, estimate DPUs, sum the DPU estimates, then use the simple formula: FPY $\approx e^{-(\Sigma \text{ DPUs})}$. The next section presents a method of applying this to assemblies and then uses Subassembly A as an example.

6.3 Method for First-Pass Yield Estimation for Assemblies

The mathematical concepts developed in the previous section can be used to implement a relatively simple method for yield estimates on new subassembly designs where PCAT process models are not yet available.

The following process is used:

1. Divide the processes required into subassembly groups as defined by the anticipated inspection and test points. These are the opportunities to discover defects.
2. Starting with the lowest level subassembly grouping(s), for each group of assembly steps leading up to a test or inspection point:
    a. List all subassemblies, all vendor parts, and all process steps required
    b. Associate the Key Characteristics with their specific subassemblies, vendor parts, and assembly process steps listed, and note anticipated process controls: fixturing, automation, etc.
    c. For vendor parts and assembly process steps, estimate the number of Defects per Unit (see DPU estimation guidance below), focusing estimation efforts mainly on the identified Key Characteristics
    d. Estimate the effectiveness of the test or inspection, that is, what percentage of the defects that arrive at an inspection point will be found by the inspection. If there is the potential that the inspection will falsely reject good parts, this number should also be estimated.
    e. Sum the estimated Defects Per Unit caught by inspection or test
    f. For each inspection point, estimate first-pass yield by $e^{-(\Sigma \text{ DPUs})}$ (DPU caught by inspection or test) plus percentage of false rejects.

3. Sum the estimated Defects Per Unit not caught and pass on this estimated DPU value to the next higher subassembly, then repeat steps 2a through 2f for that subassembly, finishing with an estimate of first-pass yield for the deliverable assembly and an estimate of DPU passed on to the next higher assembly.

A caveat to this method is that defects not caught by the final test for that subassembly will not contribute to predicted first-pass yield assigned to that subassembly. If they are caught at a test for a higher level subassembly, they would count toward the first-pass yield of that subassembly. With an effective final subassembly test, there is no ambiguity in allocation of defects. An ineffective final subassembly test may tend to overestimate the true yield of that subassembly, while underestimating the yield of the higher level assembly when the defects are finally revealed.

Estimating DPUs for parts and assembly process steps presents a challenge that requires drawing on a variety of data sources. In some cases these numbers can be fairly accurate, where there is significant historical data or pre-production processes have stabilized. Where individual process steps are already stable it is possible to use process capability analyses, such as calculating Cpk's and related DPUs by fitting Gaussian distributions to process data. Kolarik describes this process[32]. Part of this project involved researching and identifying appropriate tools that are both quick to learn and readily available to the wider Raytheon community. It was found that such analyses can be performed using SPC XL, a software add-on to Microsoft Excel that gives Cpk and associated DPU values directly. This software package is available to the entire Raytheon community through the company intranet. For someone already familiar with MS Excel, this package can be installed and Cpk analyses run with minimal effort and learning. Table 2 is a simple reference to compare DPU values with sigma capability and Cpk. A written description of process capability that roughly describes the various capability levels defined by order of magnitude DPU values.

[32] William J. Kolarik, *Creating Quality: Process Design for Results*, McGraw-Hill, 1999.

Table 2: DPU Order of Magnitude Estimates For Process Capability

Estimate of Process Capability	***DPU***	$\sigma_{capability}$	C_{pk}
Process extremely capable	1.E-06	5.07	1.69
Process very capable, easily meets specs	0.0001	3.89	1.30
Process capable with respect to specs	0.001	3.29	1.10
Process marginal with respect to specs	0.01	2.58	0.86
Process is clearly incapable of meeting specs	0.1	1.64	0.55

For the cases where good data is not readily available or reasonably obtainable, various other methods can be used to estimate DPUs. Preliminary data from preproduction runs can be used, with estimated adjustments for a production environment (ie. additional fixturing, etc. Knowledgeable engineering estimates can be applied. If data is not available, an error analysis can be performed. This involves looking at sources of errors that will contribute to defects and analyzing the relationships will combine errors to create defects.

The following section shows how this method was applied to Subassembly A.

6.4 Predicting First-Pass Yield for Subassembly A

Raytheon's PCAT software provides a powerful tool for estimating first-pass yield, but the required process capability data were not available at the time Subassembly A was being developed. Instead the method presented in the previous section was used to create an Excel spreadsheet model to estimate first-pass yield at the multiple inspection and test points for Subassembly A. KC identification indicates the elements that are most important in the predictive process, that is, key characteristics can be considered the main drivers of first-pass yield.

As a first step, Subassembly A process steps were divided into seven groups, based on six defined intermediate inspection steps and a final RF electrical test. The intermediate inspections steps included general visual evaluation and selected measurements to confirm that parts and subassemblies met drawing specifications. Excel was used to capture this information, with part and assembly names referenced by generic names to protect Raytheon proprietary information. An assembly tree showing inspection steps is given in Figure 22 and the seven tables are given later as Table 3 through Table 9.

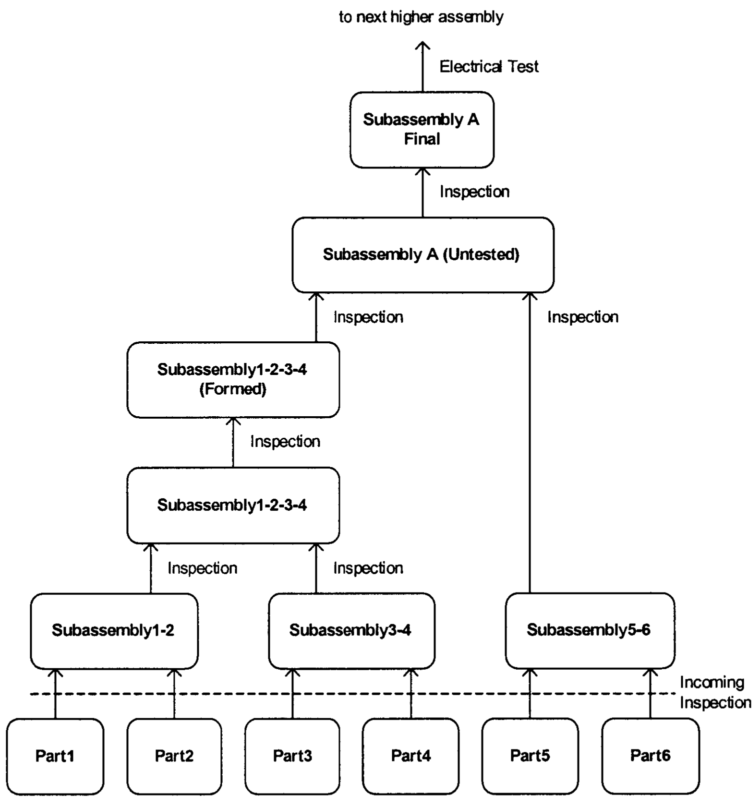

Figure 22: Assembly Tree for Subassembly A Showing Inspection Points

For each of these seven groupings, the following opportunities for defects were listed: vendor parts, lower-level subassemblies, and assembly process steps. A quantity entry indicates if multiples of the same parts, assemblies, or process steps are used. Candidate KCs and any special process controls were identified for each item before making estimates of the DPUs for each line item. DPUs considered marginal or worse (>0.01) are highlighted in the tables. Next, the effectiveness of each inspection at uncovering defects was estimated for each line item, that is, each defect opportunity. Some of these numerical estimates have been altered to protect Raytheon proprietary data, while generally maintaining the same relative trends as the original estimates.

The spreadsheet was then used to calculate a predicted DPU total for each line item (= Qty * Pred DPU), the predicted DPU caught by inspection (= Est % Defect Caught by Insp * Pred DPU Total), and the predicted DPU passed on (= Pred DPU Total – Pred DPU Caught by Inspection). Line items DPU predictions were then summed to capture two DPU subtotals, one for DPU caught by inspection and one for DPU passed on to the next higher subassembly. Predicted first-pass yield for that inspection step is given using the formula described in the previous section: FPY $\approx e^{-(\Sigma \text{ DPUs Caught By Inspection})}$. The DPU passed on are transferred to the table associated with the next higher subassembly, with the procedure repeated in each of the other tables.

As an example, we look at Table 3 that describes this process for the lowest level subassembly, labeled Subassembly1-2. Two vendor parts (Part1 and Part2) are joined using epoxy and a series of eight process steps. Predicted DPUs are low for all but the two vendor parts. It is also estimated that the inspection process has limited effectiveness, with only about a third of the total DPU caught by the inspection (.0227), resulting in a predicted first-pass yield of 97.8% for this inspection step. Closer examination shows that this is dominated by the predicted 30% inspection effectiveness rate for DPUs associated with Part2. Approximately two thirds of the total DPU are passed on to the next higher assembly (.0409), a number that is transferred to the first row of Table 5 describing the next higher assembly. This process is followed for the remaining tables. Note that defects passed through are caught at the final electrical test shown in Table 9, a definitive test for electrical performance.

Table 3: Yield Predictions for Subassembly1-2

Join Part1 to Part2 (Joint 1) to create subassembly1-2

Bond/Seal with fixture and manually injected epoxy

Vendor Parts	Qty	Pred DPU Part or Assy Step	Notes	Est % Defects Caught by Insp	Pred DPU Total	Pred DPU Caught by Inspection	Pred DPU Passed On
Part1	1	0.01	1	50%	0.01	0.005	0.005
Part2	1	0.05	2	30%	0.05	0.015	0.035
Joint 1 Epoxy	1	0.0001	3	50%	0.0001	0.00005	0.00005
Assembly Process Steps							
Clean Parts 1 and 2	1	0.0001	3	50%	0.0001	0.00005	0.00005
Assemble Masking Disk	1	0.0001	3, 8	50%	0.0001	0.00005	0.00005
Assemble Part1 to Part2	1	0.001	6, 8	80%	0.001	0.0008	0.0002
Secure Part2 in Part1	1	0.001	6, 8	80%	0.001	0.0008	0.0002
Bond Parts 1 and 2 (incl. touch-up)	1	0.001	6, 8	80%	0.001	0.0008	0.0002
Cure	1	0.0001	3	50%	0.0001	0.00005	0.00005
Defixture	1	0.0001	3	50%	0.0001	0.00005	0.00005
Inspect	1	0.0001	3	50%	0.0001	0.00005	0.00005
Subssembly1-2 Predicted DPU Caught By Inspection						**0.0227**	
Subassembly1-2 Predicted First-Pass Yield						**97.8%**	
Subassembly1-2 DPU passed on to Subassembly1-2-3-4							**0.0409**

Table 4: Yield Predictions for Subassembly3-4

Join Part3 to Part4 (Joint 4) to create Subassembly3-4
Bond/Seal with fixture, resistance tweezers, and solder preform

Vendor Parts	Qty	Pred DPU Part or Oper	Notes	Est % Defects Caught by Insp	Pred DPU Total	Pred DPU Caught by Inspection	Pred DPU Passed On
Part3	1	0.0001	3	50%	0.0001	0.00005	0.00005
Part4	1	0.004	4	80%	0.004	0.0032	0.0008
Solder preform	1	0.0001	3	50%	0.0001	0.00005	0.00005
Assembly Process Steps							
Solder Part3 to Part4	1	0.001		80%	0.001	0.0008	0.0002
Degas	1	0.0001	3	50%	0.0001	0.00005	0.00005
Inspect	1	0.0001	3	50%	0.0001	0.00005	0.00005
Subassembly3-4 Predicted DPU Caught by Inspection						**0.0042**	
Subassembly3-4 Predicted First-Pass Yield						**99.6%**	
Subassembly3-4 DPU passed on to Subassembly1-2-3-4							**0.0012**

Table 5: Yield Predictions for Subassembly1-2-3-4

Join Subassembly3-4 to Subassembly1-2 (Joints 2&3) to create Subassembly1-2-3-4
Double Bond/Seal with fixture and 1) manually injected epoxy 2) epoxy preform

Internal Parts from Previous Assy	Qty	Pred DPU Part or Oper	Notes	Est % Defects Caught by Insp	Pred DPU Total	Pred DPU Caught by Inspection	Pred DPU Passed On
Subassembly1-2	1	0.0409		10%	0.0409	0.00409	0.03681
Subassembly3-4	2	0.0012		10%	0.0024	0.00024	0.00216
Vendor Parts							
Spacer	2	0.001		50%	0.002	0.001	0.001
Joint 2 Epoxy	1	0.001	6	50%	0.001	0.0005	0.0005
Joint 3 Epoxy Preform	2	0.0001	3	50%	0.0002	0.0001	0.0001
Assembly Process Steps							
Position Subassembly3-4 in fixture	2	0.0001	3	50%	0.0002	0.0001	0.0001
Position (2) Preforms	2	0.01	6	80%	0.02	0.016	0.004
Inject Epoxy	2	0.02	6	20%	0.04	0.008	0.032
Position Subassembly1-2 in fixture	1	0.001	6	50%	0.001	0.0005	0.0005
Seat Subassembly1-2	1	0.001	6	50%	0.001	0.0005	0.0005
Cure	1	0.0001	3	20%	0.0001	0.00002	0.00008
Remove Unit From Fixture	1	0.0001	3	50%	0.0001	0.00005	0.00005
Verify Marking	1	0.0001	3	50%	0.0001	0.00005	0.00005
Inspect	1	0.0001	3	50%	0.0001	0.00005	0.00005
Subassembly1-2-3-4 Predicted DPU Caught by Inspection						**0.0312**	
Subassembly1-2-3-4 Predicted First-Pass Yield						**96.9%**	
Subassembly1-2-3-4 DPU passed on to Formed Subassembly1-2-3-4							**0.0779**

Table 6: Yield Predictions for Formed Subassembly1-2-3-4

Bend Cables to create Formed Subassembly1-2-3-4
Cable Bending

Internal Parts from Previous Assy	Qty	Pred DPU Part or Oper	Notes	Est % Defects Caught by Insp	Pred DPU Total	Pred DPU Caught by Inspection	Pred DPU Passed On
Subassembly1-2-3-4	1	0.0779		10%	0.0779	0.00779	0.07011
Assembly Process Steps							
Fixture Subassembly1-2-3-4	1	0.001		50%	0.001	0.0005	0.0005
Form 1st Long Cable (2 bends)	2	0.01	7	50%	0.02	0.01	0.01
Form 2nd Long Cable (2 bends)	2	0.01	7	50%	0.02	0.01	0.01
Offset	1	0.01	7	50%	0.01	0.005	0.005
Inspect	1	0.0001	3	50%	0.0001	0.00005	0.00005
Formed Subassembly 1-2-3-4 Predicted DPU Caught by Inspection						**0.03334**	
Formed Subassembly1-2-3-4 Predicted First-Pass Yield						**96.7%**	
Formed Subassembly1-2-3-4 DPU passed on to Subassembly1-2-3-4-5-6							**0.09566**

Table 7: Yield Predictions for Subassembly5-6

Join Part5 to Part6 to create Subassembly5-6

Bond/Seal with fixture and epoxy preform

Vendor Parts	Qty	Pred DPU Part or Oper		Est % Defects Caught by Insp	Pred DPU Total	Pred DPU Caught by Inspection	Pred DPU Passed On
Part5	1	0.0001	3	50%	0.0001	0.00005	0.00005
Part6	1	0.0001	3	50%	0.0001	0.00005	0.00005
Epoxy Preform	1	0.0001	3	50%	0.0001	0.00005	0.00005
Assembly Process Steps							
Clean Part6	1	0.001	3	20%	0.001	0.0002	0.0008
Adhere Part5	1	0.001		20%	0.001	0.0002	0.0008
Verify Position	1	0.001		80%	0.001	0.0008	0.0002
Oven Cure	1	0.0001	3	20%	0.0001	0.00002	0.00008
Remove Material	1	0.001		80%	0.001	0.0008	0.0002
Inspect	1	0.0001	3	50%	0.0001	0.00005	0.00005

Subassembly5-6 Predicted DPU Caught by Inspection 0.00222

Subassembly5-6 Predicted First-Pass Yield 99.8%

Subassembly5-6 DPU passed on to SubassemblyA 0.00228

Table 8: Yield Predictions for Subassembly A (Untested)

Join Subassembly5-6 to Formed Subassembly1-2-3-4, then Touch-up to createSubassembly A

Bond/Seal with fixture, solder preform, and resistance tweezers

Bond/Seal with fixture, pretinned solder pad, and manual solder iron

Bond/Seal manually with epoxy

Internal Parts from Previous Assy	Qty	Pred DPU Part or Oper	Notes	Est % Defects Caught by Insp	Pred DPU Total	Pred DPU Caught by Inspection	Pred DPU Passed On
Formed Subassembly1-2-3-4	1	0.09566		10%	0.09566	0.009566	0.086094
Subassembly5-6	1	0.00228		10%	0.00228	0.000228	0.002052
Vendor Parts							
Joint 5 Solder Preform	2	0.0001	3		0.0002	0	0.0002
Assembly Process Steps							
Set-up Holding Fixture	1	0.001		50%	0.001	0.0005	0.0005
Position Subassembly5-6	1	0.001		50%	0.001	0.0005	0.0005
Secure Subassembly5-6	1	0.001		50%	0.001	0.0005	0.0005
Position Solder Fixture	1	0.001		50%	0.001	0.0005	0.0005
Solder Cables	2	0.001	6	50%	0.002	0.001	0.001
Reposition Fixture	1	0.001		50%	0.001	0.0005	0.0005
Solder Center Conductors	2	0.005	6	50%	0.01	0.005	0.005
Degas	1	0.0001	3	50%	0.0001	0.00005	0.00005
Touch-up	1	0.001		50%	0.001	0.0005	0.0005
Cure	1	0.0001	3	50%	0.0001	0.00005	0.00005
Inspect	1	0.0001	3	50%	0.0001	0.00005	0.00005

SubassemblyA Predicted DPU Caught by Inspection 0.018944

Subassembly A Predicted First-Pass Yield 98.1%

Subassembly A DPU passed on to Tested Subassembly A 0.097496

Table 9: Yield Predictions for Tested Subassembly A

Electrical Test

Internal Parts from Previous Assy	Qty	Pred DPU Part or Oper	Notes	Est % Defects Caught by Test	Pred DPU Total	Pred DPU Caught by Test	Pred DPU Passed On
Subassembly A	1	0.097496		99%	0.097496	0.09652104	0.00097496
Test Process Steps							
Calibrate Test Station	1	0.01	6	80%	0.01	0.008	0.002
Place Part in Test Fixture	1	0.02	6	80%	0.02	0.016	0.004
Run automated test software	1	0.0001		50%	0.0001	0.00005	0.00005

Tested Subassembly A Predicted DPU Caught by Inspection 0.12057104

Tested Subassembly A Predicted First-Pass Yield 88.6%

Tested Subassembly A DPU passed on to Next Higher Assembly 0.00702496

6.5 Comparing Predictions to Actual Yields

Table 10 presents a summary of the predicted first-pass yields for the inspection steps, compared against actual yield data collected during the Proof of Manufacturing run. It appears that this method was effective at estimating first-pass yields within about a 5% band. The most significant observation is that the intermediate inspections are relatively ineffective at detecting defects, which are not revealed until the final electrical test. Yields for intermediate inspection steps are in the high 90%'s, while the final test yield is much lower at 91%. Looking at Table 3 through Table 9, the model shows how defects are passed through the initial and intermediate inspection steps and caught only at the final RF electrical test. This highlights the potential for improvement if an effective test could be implemented earlier in the assembly process. It is also worth examining whether all inspection steps are cost-effective. For example, the final inspection of Subassembly A before going through test shows a 99% yield. If the same defects that are identified here would be revealed by the final electrical test, then in full production it would be more cost effective to skip this last step and proceed directly to electrical test.

The final electrical test is considered very effective (see 99% effectiveness estimate in Table 9), meaning that very few defects are expected to be passed on to the next higher assembly. As noted when this method was presented in Section 6.3, if this final test were less effective, then these yield numbers may need to be adjusted to account for those defects that would be discovered later in the assembly process or by the customer.

Table 10: Predicted First-Pass Yields Compared to Actuals for Proof of Manufacturing (POM) Run

Inspected Subassembly	Predicted First-Pass Yield for POM	Actual First-Pass Yield during POM
Subassembly1-2	97.8%	95%
Subassembly3-4	99.6%	95%
Subassembly1-2-3-4	96.9%	97%
Formed Subassembly1-2-3-4	96.7%	96%
Subassembly5-6	99.8%	98%
SubassemblyA (untested)	98.1%	99%

Tested SubassemblyA	88.6%	91%

Note: Relative numbers are representative, with offsets applied to protect proprietary data

This model is for a snapshot in time and can be updated during the transition into production. For example, the numbers shown here represent predictions and actuals for the beginning of the Proof of Manufacturing run. With iterative improvements in the production process and tuning of the test specifications, production yields at test were consistently near 100%. If it can be shown that yields are consistently near 100%, it may be possible to reduce or eliminate the costly final testing if it can be verified that processes remain in control.

In summary, this model provides a way of looking at buildup and removal of defects through a process of multiple inspections that are characteristic of new radar subassembly designs. Achieving reasonable overall yield estimates can be accomplished by breaking the model into the many line items that describe opportunities for defects, then using KCs to identify those that deserve the most effort in estimating individual DPU numbers.

6.6 Modeling Manufacturing Processes

This project began with a goal of achieving better manufacturing system predictability through greater accuracy in manufacturing process simulations. Asking a series of "Whys?" led down a path that focused on enablers for more accurate models by first looking at KCs as the basis of a "predictability chain" and then developing a structured method to estimate first-pass yields. Taken alone, accurate yield estimates are an important part of predicting how a manufacturing system will perform. They are also an important input to manufacturing process models that can be used to predict other measures of interest.

Raytheon has developed significant capabilities in modeling manufacturing system processes for radar subassemblies at their Andover facility. A prior MIT Leaders for Manufacturing student, Tim Sweitzer, addressed this topic in detail during a project at Raytheon's Andover facility in June-December of 2001. Sweitzer introduced the use of *Process Model*, a commercial package that provides a software environment to visualize, analyze, and improve processes[33]. This software allows one to model many of the

[33] *ProcessModel* Version 4.2, ProcessModel Corporation, Provo, UT, website http://www.processmodel.com.

complexities of manufacturing system processes that drive performance measures (ie. queues, rework, work-in-progress, non-value added activities, resource requirements, batching, etc.). In his thesis[4], Sweitzer presents an initial model of the manufacturing system for an earlier version of the same Subassembly A design examined here.

As this project neared completion, Raytheon personnel were updating the initial manufacturing process models to include changes to the product and process design. These models were used to predict full-rate performance of the line and incorporated into the training process to demonstrate full-rate performance on the actual line. This thesis will not present further details on modeling of manufacturing processes, but does highlight that accuracy of these models is dependent on enablers such as the identification of KCs and estimation of first-pass yields as enablers.

Section 7: Recommendations and Organizational Change

7.0 Section Overview

This section will summarize recommendations, address the strategic benefits of these changes, examine the cultural environment for implementation, and outline a transition plan for future work.

7.1 Summary of Recommendations

This project proposes that better predictability of manufacturing system performance of new radar subassembly designs can be achieved by integrating the following elements into the product development process:

- Implement key characteristics identification as an integral part of the product design process. This is considered the most significant recommendation, as this is not presently part of the development process for radar subassemblies manufactured at Raytheon's Andover facility.
- Use the methods presented in Section 4 to verify if candidate KCs are truly KCs and to validate Cpk estimates for processes.
- Use the KC identification exercise as an opportunity to review tolerances and associated process controls. If parameters thought to be key show little impact on customer-required performance, this indicates an opportunity for cost savings by relaxing tolerances and thus reducing scrap or rework. Inspection and other process controls may also be reduced or eliminated.
- Obtain more accurate first-pass yield estimates through PCAT models or the custom yield models previously presented, where the KCs indicate the product and process features that will have the greatest impact on yield. This is considered an extension of existing work.
- Apply these first-pass yield estimates in manufacturing system simulations using existing software tools like the *Process Model* software previously introduced. This is considered an extension of existing work.

7.2 Strategic Benefits

Strategic benefits of implementing the proposed methods can be grouped in three categories: benefits specific to a new subassembly design, benefits at a system-level, and benefits in building organizational capabilities.

7.2.1 Benefits to Subassembly Designs

Subassembly designs can directly benefit from cost and performance improvements resulting from the methods proposed. In particular, a culturally established method of identifying, verifying, and communicating KCs helps focus the concurrent design process on features that have the strongest cost-performance tradeoffs. When such priorities are communicated to all development team members, including process design, process implementation, and training personnel, it can decrease development time, reduce product redesign cycles, and result in more efficient process and manufacturing system design.

As demonstrated in the case of Subassembly A, identifying and verifying KCs reveals that many of the product and process features initially thought to be critical may in fact have little or no impact on customer required performance. When this is the case, it may be possible to justify the relaxation of specifications. For internal manufacturing processes this can reduce the need for inspection, scrap, and rework. For vendor parts this may allow suppliers to reduce their costs. Process controls may also be avoided, or substituted with less expensive measures. Inspection may be reduced to a sampling level required to be sure that processes stay in control. For radar subassemblies, process control is a significant cost, as it often involves many specialized precision fixtures for assembly, bond, and cure operations. For cases where KC verification confirms that variation of a feature within specs does have a significant impact on performance, process controls can be applied if the improvements merit the additional cost of the controls. Including KC verification as part of the process also provides a feedback measure of effectiveness for the initial KC identification. As KC identification is improved through the use of better analytical techniques, the verification stage will help track this progress and drive continuous improvement.

Supplier issues were found to be the main cause of delays when Subassembly A was transitioned into production. KC flowdown to suppliers is one tool for effective management of supplier quality, communicating features where process controls are particularly important. For example, each feature identified as a KC could trigger a requirement that suppliers either demonstrate a certain process capability level (ie. Cpk > 1.3) or implement 100% inspection.

7.2.2 Benefits to Systems

Achieving predictable performance from a subassembly and its manufacturing system also provides benefits at the radar system level. As system architecture is defined and development moves from preliminary to detailed design, error budgets are allocated to each subassembly. Predictions of yields and other manufacturing system performance measures would permit strategic reallocation of error budgets to optimize the radar system. The objective may be minimizing overall system cost for a given set of customer performance requirements. In some situations it may be preferable to maximize system performance for a given cost target, for example, on demonstration projects where future contracts will be awarded on the basis of performance relative to a competitor's system.

7.2.3 Organizational Benefits

More predictable manufacturing systems also enable Raytheon to make better business-wide decisions. Understanding internal manufacturing capability permits better make-buy decisions across a business unit or the entire company. Specifically, KCs identify those processes most critical to radar system performance. This is important information when determining whether to develop key supplier relationships or allocate strategic capital where it has the greatest payoff in terms of building internal design and manufacturing capability.

7.3 Organization & Change

Raytheon's Andover facility provided an excellent opportunity to view the challenges of implementing change at a large company. The most significant change initiative associated with the project is the recommendation that KC identification be implemented as a part of the product development process. This initiative is discussed using a framework of three different perspectives on organizations: strategic, political, and cultural.

7.3.1 *Strategic Perspective*

Historically Raytheon has excelled on a strategy of providing superior technical solutions. Founded in 1922 as the American Appliance Company, it has a long history of technical achievements in radio tubes, radar technology, inventing microwave cooking, and developing the first guided missile that could hit a flying target[34]. Defense contracts, typically structured on a "cost-plus" basis, were typically won on the basis of technical reputation and performance.

However, this environment is changing. The past few years have seen a consolidation of companies within the defense industry. Competition is more intense for development programs. Government agencies that issue contracts are now placing more emphasis on commercial practices, including operational excellence. Product development time and manufacturing issues are increasingly important. In this new environment, being a technology leader is not enough.

Raytheon has implemented a number of strategic initiatives to remain competitive. Many of these fall under the umbrella of the Raytheon Six Sigma program, discussed below in the section on culture. These initiatives have shown results, particularly in applying lean manufacturing techniques on the factory floor. There is strong top-level support for major initiatives beyond the factory floor, with expectations of similar productivity gains possible in the development process.

During the internship project, Raytheon announced a major reorganization of its defense businesses. With this announcement, the Andover facility became the Operations center for the new Integrated Defense Systems (IDS) business unit. The details of the reorganization were still underway at the completion of the internship in December 2003, and it remains to be seen what effect this will have on lower levels of the organization.

From a strategic perspective, the identification of KCs fits well with corporate Six Sigma initiatives, and allows Andover Operations to lead an initiative that ties improvements in manufacturing back to the product development process.

7.3.2 *Political Perspective*

Organizational structure at Raytheon is a mix of functional and project oriented organizations. The structure was traditionally functional, led by design engineering, which

[34] Historical information from Raytheon website: http://raytheon.com/about/history.htm

still retains much of the organizational clout. Several people expressed the view that manufacturing engineering and operations were gaining strength, but are still considered less important. Project leaders are given responsibility to coordinate projects across the functional boundaries. A recent addition to the organizational mix is the concept of value-stream leads. These leaders take responsibility for an entire value stream within the Andover factory.

This project was conducted under the supervision of the Surface Radar Operations Group. Residing in the Andover plant, this group is closely linked with the manufacturing organization. Development engineering work began at a nearby facility in Sudbury, Massachusetts, with design engineers moving to the Andover factory as the design began transitioning into production. As an intern with no direct authority in any organization, I had an excellent opportunity to neutrally view an initiative from multiple organizational perspectives.

Implementation of KCs identification would provide benefits across organizational boundaries. It would mean a better understanding of manufacturing issues before new designs go into production, avoiding the headaches of reworking a design already in production. Raytheon has been moving toward concurrent product and process design for radar subassemblies, and identification of KCs can provide a strong link between the engineering and manufacturing organizations as it cuts across these boundaries.

The design engineering organization will bear most of the costs of implementing KC identification. It will require additional analysis and more coordination with the manufacturing organization. In the past, there may have been less incentive for design engineering to take on this extra work, as they held less responsibility for the transition to production. But trend is moving toward the design community sharing in production risks. Design engineering is now assigned in the factory until production of the new design is going smoothly, creating a strong incentive to implement tools to ease this transition to production.

7.3.3 Cultural Perspective

Soon after Dan Burnham became CEO of Raytheon Company in 1998, he launched the Raytheon Six Sigma (R6σ) program as an initiative to establish a company-wide culture. At the most general level, R6σ is based on a six-step process for continuous improvement: Visualize, Commit, Prioritize, Characterize, Improve, and Achieve. Its charter is much broader than the statistical methods that its name implies, and includes many other best-practices. For example, R6σ includes many of the principles of lean manufacturing as embodied in the Toyota Production System.

Raytheon management has demonstrated serious commitment to R6σ through extensive training and certification programs for a large number of employees, spanning top leadership to the hourly workforce. Many Six Sigma projects have achieved success in increasing productivity through process improvement on the factory floor, but with relatively less involvement from the design engineering community. Raytheon has recently launched a Design for Six Sigma (DFSS) initiative, specifically targeting the design engineering community in an effort to achieve similar productivity improvements through better product design. Just as this project was ending, the Integrated Defense Systems (IDS) organization was soliciting suggestions for DFSS initiatives.

The Six Sigma program backdrop provides an excellent environment for the success of a KC implementation program. The initiative to identify KCs can take advantage of timing with the cultural push toward DFSS.

Raytheon also has a one-company initiative for knowledge sharing and dissemination of best practices. Knowledge is captured and made available through the Raytheon intranet. A major part of this initiative is a generic development process template, called the Integrated Product Development Process (IPDP), which covers the lifecycle of a program. Development of radar systems follows this process, which is tailored for specific program needs. A high level view of the IPDP is shown in Figure 23. Business strategy and planning drive the development of product requirements and architecture, with a specifications flow-down to the subsystem and component level. Detailed design of specific subassemblies occurs concurrently with the design of associated manufacturing processes. This is represented by the dotted boxes in Figure 23. While these dotted boxes are not part of Raytheon's top-level IPDS view (but perhaps should be), they represent concurrent engineering functions that are part of the existing lower-level hierarchy. After system verification, these subassemblies are transitioned into production, then integrated into deliverable systems. The product that reaches final production may have been through a number of iterations.

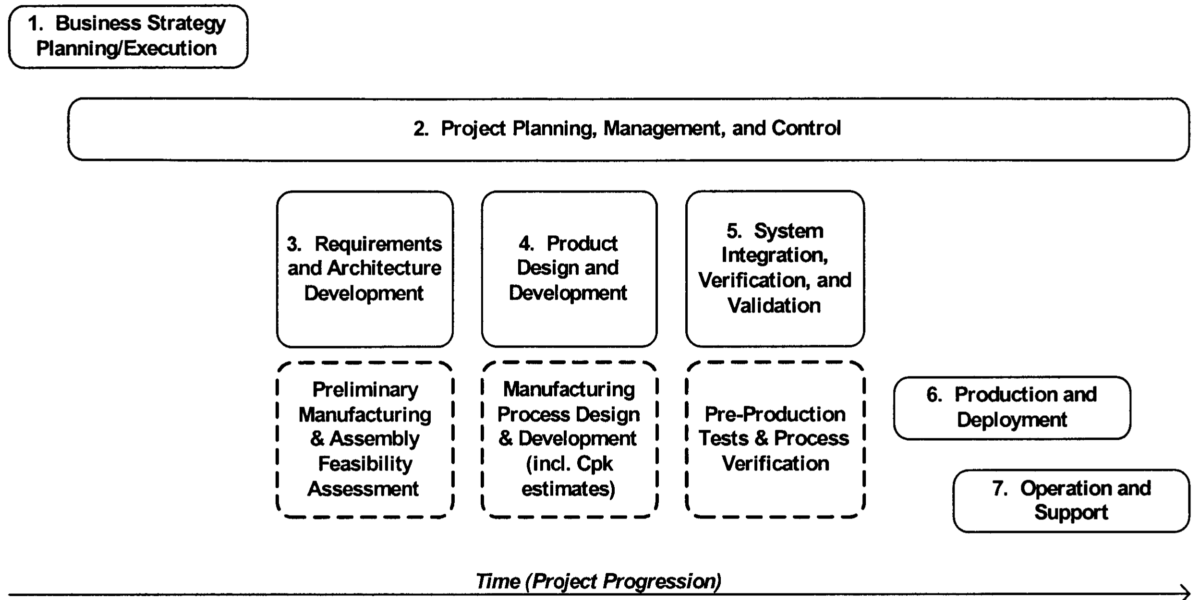

Figure 23: Raytheon Integrated Product Development Process (IPDP)

KC identification does not yet appear as part of the lower-level IPDP documentation. It fits well into this framework, specifically in the lower-level processes in area 3. Requirements and Architecture Development, and area 4. Product Design and Development. Incorporating KC identification into IPDS gives it broader visibility across the company so that improvements to the process can benefit from a broad range of applications beyond just radar subassemblies.

7.4 Transition Plan

Changing the product development process for radar subassemblies to include the identification of KCs will not happen on its own. This project has identified the opportunity for improvement, looked at some of the tools and resources available, and has demonstrated some of the challenges and benefits with application to Subassembly A. Before leaving the internship, a transition plan was recommended with plans for future work, including the following actions:

- A new development program was identified to initiate the implementation of KC identification.
- KC identification was proposed as a DFSS initiative.
- IPDP implementation of KC identification was discussed with IPDP content owners.

- Training opportunities were identified for the Raytheon Key Characteristics Designation System (KCDS) currently applied at the Tucson facility.

A major step still required for success is to identify a knowledgeable and authoritative champion for KCs. This has been done at Raytheon Missile Systems in Tucson, and may provide a model for implementation within the Integrated Defense Systems organization.

Implementation of the other project recommendations will be easier as they are extensions of existing work. Estimates of first-pass yield for radar subassemblies will be enhanced with the use of Process Capability Analysis Toolset (PCAT) models that are currently being updated. These will include information on electromechanical assemblies such as Subassembly A. This project provides a spreadsheet model for predicting yields where such models are not yet available. Modeling of manufacturing processes using *Process Model* is underway, with many users trained and multiple licenses available. This project simply provides more accurate inputs to these models.

Section 8: Conclusions

Subassemblies for new radar system designs present challenges in predicting manufacturing performance earlier in the product development process. Often the product performance is a function of many variables, and the tendency is to identify too many features as key with providing supporting data and analysis. Finding those features that truly have the greatest impact on product performance and are simultaneously at risk due to process variation may be difficult, as experienced with the KC identification exercise for Subassembly A.

The KC identification process for Subassembly A would have benefited from additional analytical methods to better understand the variables that drive performance. In the case of assemblies designed to operate at high frequencies, numerical simulations such as finite element methods are invaluable, but often have difficulty in capturing the many small nuances in design features that can combine to impact performance. In this case a rigorous analytical evaluation of pre-production prototype hardware is needed. Design of Experiments is one of the most powerful tools available, but requires that sufficient time and cost are budgeted into the development plan. One of the challenges with DOEs is that early in development it is often difficult to quickly get quality vendor parts with parameters accurately tailored to the desired levels.

Sources of variation in measurement are also important. While care was taken in performing mechanical measurements and electrical tests, measurement capability studies (i.e. Gage R&R methods) are needed to properly indicate expected performance variation due to measurements.

Identification and verification of KCs is most effective if treated as an integral part of the design process and considered in the flowdown of requirements to subsystems and components. Naturally this should be started early. This includes the flowdown of KCs to vendor supplied parts. Primary KCs will be associated with customer requirements. For derived KCs it should be remembered that these are artifacts of the design concepts. If there is difficulty in meeting a derived KC, it is worthwhile to examine whether an alternate design with different KC chains may make it easier to achieve the primary KCs.

It is not uncommon in complex and state-of-the-art radar system assemblies that there will be intriguing interdependencies among many diverse product and/or process parameters that are not readily modeled and may not be characterized sufficiently to result in desired precision when performing predictive product/process simulation for manufacturing. A typical reaction is to set specifications at or even beyond the limits of present process capability, resulting in significant increased cost when in reality there may be little benefit to product performance. Analytical verification of the impact of variation on performance provides a significant opportunity for cost savings.

A general observation is the need to continue positive steps toward concurrent engineering. When issues arise in the development process, one still hears "Is it a design or process issue?" The answer is usually "Yes, it's both." Identification of KCs cuts across these boundaries and will result in higher performing products at a lower cost.

In conclusion, including the identification of KCs in the product development process enables a better understanding of which product features are driving yields. Better yield estimates enable more accurate manufacturing system process models that in turn provide the predictable manufacturing performance measures that are needed for better strategic business decisions.