

**Manufacturing Operation Modeling for Product Redesign:
Resistance Analysis of Low-Temperature Co-fired Ceramic Circuits**

by

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Abstract

When bringing a new or improved product to market, a design and manufacturing enterprise can shorten time to production and improve results by understanding and designing within the constraints of the manufacturing process. However, characterizing models describing process and product variable relations are often poorly defined or not readily applicable to the actual manufacture of a product or to a variational design. Hence, quantitative redesign information may be lacking. Even when statistics can describe product performance based upon manufacturing variables, there is frequently little feedback to designers about limitations of current processes in producing more optimal output. Also, in a real industrial enterprise, social and managerial problems drive any such design-for-manufacturing integration modeling. Modeling and experiments are limited to activities that provide direct answers to short-term identified problems. This means that only a continuous improvement and iterative approach is practical to constructing process constraint models.

Considering both technical and non-technical limitations, a methodology is developed to quantify the quality constraints imposed on product design by its manufacturing process. The sequence of operations transforming incoming material into the final product is diagrammed into a topology of the operational sequence. Next, performance metrics are identified corresponding to customer requirements. Using engineering analysis, a basic model relating known variables to the metric is validated with production data, either from designed experiments or from product sampling. Modes of impact of each operation upon the metric are conceived and can be integrated into the basic model. This refinement in the manufacturing model results in higher process capability. The methodology, therefore, is one of continuously improving the understanding of the process-imposed constraints to improve the product.

The methodology is applied to a case-study of an actual manufacturing system. The field of low-temperature co-fired ceramic (LTCC) circuits has supported the manufacture of successful hybrid microcircuitry products. However, the technology of LTCC buried resistors, resistors printed and fired on internal layers of circuit laminates, is not well understood. Previous efforts to minimize variation in resistance from target values have been sparse and unrevealing. Current practice requires the manufacturer to increase production volume, and thus cost, to satisfy customer demands, as few laminates of buried resistor configuration achieve the functional requirements. Therefore, a predictive model of resistor behavior incorporating manufacturing operation concerns is essential to increasing yield and improving performance in redesigned hybrid circuits.

Thesis Supervisor: Kevin N. Otto
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Thank you, Mom and Dad, for always supporting me. Forgive me for not often traveling home to thank you in person. As you review the results of my months away, remember that I invest some of myself into everything I do, honoring the way you raised me.

Many thanks to my brother and sister, and my relatives, who often appreciate my education and opportunities more than I do. Their perspectives and insights encourage me to make the most of my God-given talents and potential.

I'm grateful to Kevin Otto, my advisor who took a chance by signing me as his first graduate student. I hope I'm accomplishing as much as you had hoped that day you contacted me in England. We've come a long way, and I'm looking forward to our future endeavors.

Much appreciation goes to my friends and colleagues who make the occasional social outings and written correspondences possible.

Also, thanks to my alma mater Caltech, which helped prepare me to properly set forth on this journey, and to the special friends I made there who continue to welcome me with open arms.



(That's me in the upper right. - C)

My father occasionally tells me about his days at Temple University and dental school. The bitter cold weather. The poverty which his graduate student life seemed reminiscent. And the character-building experiences. Through all that and more, nothing prevented him from proving the nay-sayers wrong, rising through U.S. Navy ranks, or going on to bigger and better things....

Now I know what he means by perseverance. Amazing what the line "I like it" can do when repeated over and over again as one faces the lonely Friday evenings in the office or the morning after another all-nighter. From the looks of it, I'll be saying it for years to come. Wish me luck, y'all.

-from personal memoirs

Tell me and I'll forget.
Show me and I may remember.
Involve me and I will understand.

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Chapter 1

Introduction

The demanding nature of today's market requires design and manufacturing enterprises to deliver new and improved products while using limited resources [Ashley, 1990] [Fitzgerald, 1987] [Gardner, 1992]. This demands optimal use of current facilities and an ability to vary output without sacrificing quality. Understanding the capability of the manufacturing system and providing a means to continually improve process capability are essential for survival in the competitive marketplace.

This thesis considers the technical and non-technical issues of qualitatively representing and quantitatively characterizing a manufacturing system. A methodology is presented that directs efforts to investigate and model the operations that transform incoming materials into a finished product, thereby providing a framework in which an enterprise can determine the quality constraints imposed by its manufacturing processes.

The first chapter introduces the motivation behind the research in manufacturing operation modeling. Section 1 reviews the type of problems for which the research is directed, and Section 2 further defines the purpose of a methodology and its intended benefits. The organization of the thesis is outlined in Section 3, with thesis conventions noted in Section 4.

1.1 Research Motivation

Manufacturers strive to make the best product in the shortest time at the lowest cost. In a competitive industry, these goals drive the actions of the companies; those

that perform in superior fashions have the advantage in the marketplace, and thus can realize greater success and stability. However, the path to producing high-quality goods with short times-to-market is not well-established. While general best-practices and guidelines exist to assist in the optimization and improvement of production [Boothroyd, 1991] [Carlson, 1994], there is still the need for a directed approach or methodology that attempts to achieve the quality, cost and production goals for a given manufacturing system which also offers continuous improvement possibilities in the future [Gardner, 1992].

In industry there are often systems which are insufficiently understood, and the manufacturing processes and their effects on incoming material can be extremely difficult to quantitatively describe, or model. In some cases, the significant process and material variables are not known to the designers, engineers or manufacturers. In other cases, characterizing equations describing product and process variable relations are unknown, poorly defined or not readily applicable to the actual manufacture of the product or a slightly different configuration of a product. Sometimes the amount of data and the quality of the data taken is incomplete or inefficient. In any case, quantitative design and redesign information is lacking for a given factory system.

A realistic scenario, which is actually occurring at established companies in the United States, involves the collection of data of questionable utility. In two leading manufacturing firms reviewed during this research, the data collection capabilities are only now going on-line, and the usefulness of the information collected was in doubt from the very beginning of the testing. The causes of poor data collection stem from not only limitations in technological comprehension and measurement capabilities, but also from non-technical issues, such as budget- and time-constraints, personnel issues and management decisions. For example, a production facility currently under study is attempting to improve one of its technologies, but cannot stop production to accommodate a more complete design-of-experiment than it actually conducted, due to the company requirement to make sufficient volume of a working product using the same facilities and machines. The set of data produced by that design of experiments is limited in potential, but was considered the best possible experiment at the time, given all the technical and non-technical constraints.

As another example of a non-technical constraint, consider the following: management believes that the need for a more time- or cost-intensive experiment must be justified by some other evidence. That is, company concerns may require that some other studies show that a proposed experiment "must" be done, and that without that initial evidence, the complete experiment is "not necessary" or "not cost-effective" from

the perspective of the managers. A way to provide this evidence is to attempt to conduct analysis based upon non-optimal data and information, and somehow justify a more complex experiment on those incomplete studies. There is the need for a methodology that directs efforts of analyzing manufacturing to provide justification for other experiments.

The complexity of manufacturing systems and the lack of communication between work groups each responsible for a separate part of the system creates another barrier to fully understanding where critical operations occur. Seldomly is there a technical authority on all processes occurring in a system. Thus, there needs to be a robust methodology that different workgroups and teams can use independently of one another, and, when combined, will be a useful tool to compare and troubleshoot completely different manufacturing operations within a system. The end result should be a useful mapping, simplifying the large number of subsystems, with a hierarchical structure to allow for varying requirements of information upon request.

Consequently, a methodology is desired that addresses the following:

- Directs analysis of present data to identify where limited resources should be used for additional experiments
- Simplifies the representation of a manufacturing system that supplements efforts to understand operations and critical processes
- Allows for continual development as new information, requirements and processes are added.

1.2 Background of Quality

Efforts in industry center around the pursuit of quality. In the last two decades, there has been a shift in the definition of quality recognized by American industry. One such illustration is the often used example of color television sets as produced by Sony-USA and Sony-Japan¹. Although the American plant produced merchandise to specification with zero defects, more customers perceived their sets to be of lower quality. The Japanese sets met specification the majority of the time, but the deviation from targeted color density was smaller than the American counterparts, and more customers were pleased with their merchandise.

This example, illustrated in Figure 1.1, introduces the concepts of *target value* and *variation*. The Japanese manufacturer produced higher quality products overall

¹ as first presented in the newspaper *Asahi*, April 17, 1979, and cited in many textbooks such as [Phadke, 1989] and [Clausing, 1994]

because its factory output probability density function (*pdf*) peaked and centered about the target color quality, while the American products performed on target less often, even with color density always with the lower and upper specification limits (*LSL* and *USL*) Since then, the value of reducing variation has been recognized worldwide as equally important, if not more so, as producing zero defects.

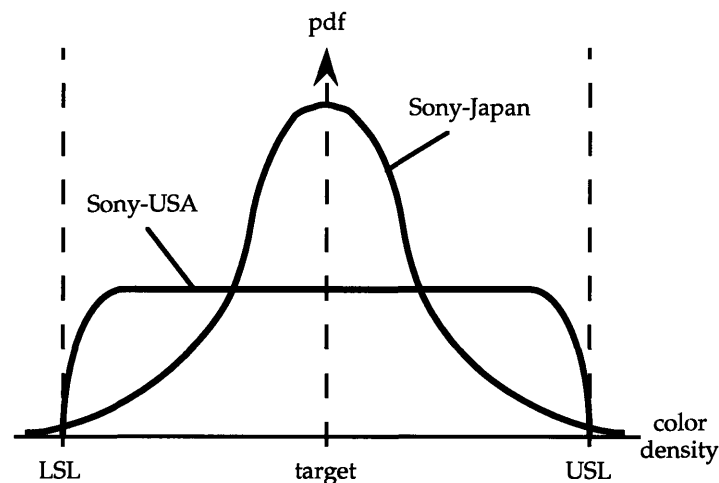


Figure 1.1: Quality as it relates to meeting specification and deviation from target. Sony-Japan satisfied more customers despite having some products not meeting specification. Sony-USA had zero defects, but met ideal customer standards on fewer occasions.

1.2.1 Deming and Taguchi

In the early 1950's, as included in his fourteen "points for management," Dr. W. E. Deming believed in two particularly relevant concepts for quality:

- Create constancy of purpose for continual improvement of product and service
- Improve constantly and forever the system of production and service.

Deming's philosophy as implemented in Japan over the last forty years helped Japanese industry grow from its wartorn state to a leading world power in production. Deming recognized the importance of continuous efforts to improve quality, as opposed to imposing a one-time standard and never striving to achieve better.

One definition of quality was established by Professor Genichi Taguchi, a proponent of Deming's philosophy, as the loss a product causes to society after being shipped, other than any losses caused by its intrinsic function. Using what is termed a

quality loss function, this definition implies that the minimization of variation is more useful than achieving strictly conforming to tolerance standards.

The standard measure of deviation, defined as *sigma* (σ), is used in quality control throughout the world. Industry is shifting from three sigma quality standards (99.73% within specification) to six sigma standards (>99.99% within specification) in following the philosophy of *continuous improvement*.

1.2.2 Predictive Model of Output

Manufacturing relies on transforming materials into desired end states in a consistent fashion. Implementing scientific models and empirical trials, a factory makes parts to meet its criteria, its target values. However, when the products fail to meet specification, the predicted output of the manufacturer has not been achieved for some reason. When a part does not match the predicted output, the predictive model for the part may not be accurately describing the actual overall process in sufficient detail, or there is too much variation in the process that consequently produces defects.

The former possibility, when the descriptive model of the manufacturing process is not accurate, requires investigation into the sources of error in the predictive model. Process effects which are not accounted for in the model must be traced and included in subsequent production runs. When sufficient sources of this type of "error" from the original model have been included in the modified predictive model, factory output may very well fall within specification, even with any variation inherent in the process not due to an uncharted operation effect. This is equivalent to saying the predicting model $y=fnc(\{x_i\})$ is based upon and accurate to first-principles, but second-order effects of the same magnitude as the tolerances are causing the unacceptable output.

Thus, suppose the manufacturing system may initially be described as:

$$\text{output} = (\text{basic model}) + \text{"error"}$$

Upon further investigation, if it is determined that a process effect previously unknown and of lower magnitude to the basic model is causing product output to deviate from expectation, if:

$$\text{"error"} = (\text{process effect}) + \text{error}(\text{variation})$$

then the modified predictive model becomes:

$$\text{output} = (\text{basic model}) + (\text{process effect}) + \text{error}(\text{variation})$$

What had previously been considered error in production has now become part of the model of the manufacturing system. As error term limit specifications become increasingly smaller, identifying secondary process effects grows in importance.

1.2.3 Variation Reduction

Reducing the variation of output from the target value is similarly important to ensuring quality. Supposing that the predictive model includes all traceable process effects other than noise in the system, the task of reducing the effects of variability becomes necessary towards improving product quality. Understanding the predictive model, and including significant process effects in that model, are paramount in reducing variation, as this model combined with the variation in inputs result in the variation in output.

For example, given independent input parameters x_i , and a predictive model $y=fnc(\{x_i\})$, and assuming normal distributions in input variations σ_{x_i} , the output variation σ_y is given approximately by:

$$\sigma_y = \sqrt{\sum_i \left[\left(\frac{\partial y}{\partial x_i} \right)^2 \sigma_{x_i}^2 \right]} \quad (1.1)$$

Therefore, an accurate model of y in terms of input parameters x_i is needed in order to investigate ways to limit contributions from σ_{x_i} by implementing alternate processes that are less sensitive to input parameter variations, thereby decreasing σ_y .

Factory limits may determine how small the variation in a given parameter can be controlled, so it may be more feasible to change the operation or process that multiplies the variation resulting in the output variation. Or, if the operation is not adjustable or changeable due to, say, cost reasons, an alternate material with lower variability and lower equivalent cost may be the solution. Again, however, an appropriate descriptive model of the manufacturing process is essential towards providing possible solutions to a quality control problem.

1.2.4 Variety

Although not necessarily considered a facet of quality, the idea of product variety is nonetheless a measure of a manufacturer's ability to satisfy the customer. Consumers want and need varying configurations and different sets of options in their products, and a manufacturer that can provide a variety of products to a market has yet another advantage over competitors that cannot.

Variety, however, often must be achieved using the same machines and processes for all of the models, as a factory can usually not afford to have separate systems for product similar in nature. Thus, differing features on one option must be produced by

changing only some of the input parameters, such as material or a few machine settings, while the majority of the variables remain the same while applying the same physical process.

Therefore, as a company tries to introduce a new option and increase the variety of its output, the manufacturer relies on the adherence to the predictive model and the control of variability in output using perhaps only slight changes in input values. Without an appropriate descriptive equation relating input to output variables, it may be very difficult for the company to easily accomplish its goal at the different settings. The manufacturer relies on complete, or at least adequate, quantitative understanding of the processes involved in its production facilities. It needs to know its current limits of production and parts of the system most likely to introduce failure components so as to avoid costly initial runs and experimentation before the first useful product is made.

1.3 Thesis Overview

Following this first chapter, Chapter 2 reviews methods currently used in industry. Some of these tools focus on organizing information about a product and its functionality and failure; others are based in mathematics and statistics. These tools are briefly described to give the reader an idea of their nature and applicability.

Chapter 3 presents the methodology that is at the heart of the thesis research. A detailed review of its principles are discussed and illustrated in both qualitative and quantitative fashion. Discussion is kept to a generalized level of applicability, allowing the concepts shown to be implemented to any given process.

A case study is presented in Chapter 4, in which the concepts of Chapter 3 are specifically applied to a real-world manufacturing system. Actual numbers and figures are presented, and are intended to demonstrate the potential of the methodology. Additional work on the case study is also proposed to further illustrate the methodology.

Future research endeavors are discussed in Chapter 5. Conclusions and the achievements of the current work are also given.

1.4 Notation and Conventions

In the following chapters, the author has attempted to maintain consistency in the use of symbols and formatting.

- Subscripts identify a index of a variable. For example, x_i indicates the i th component of the vector \vec{x} or the i th unit of a sequence of x 's.
- Keywords and terms of particular importance are printed in *italics*.
- Mathematical or logical expressions are shown separately from body text.
- Diagrams and pictures are labeled as "Figure #.#"; equations as "(#.#)"; tables as "Table T#.#" or "T#.#".

Chapter 2

Current Practices of Quality Design

Ongoing research in design and manufacturing strives to improve production and process modeling. Present-day tools have also proven to improve quality and efficiency, and many have become standard tools in design and redesign. Using flowcharts, specialized tables and diagrams, and statistical and mathematical tools, these methods direct manufacturers' and design teams' efforts and resources towards optimal and robust design. Parts of these same procedures contribute to the development of the methodology presented in this thesis.

2.1 Related Work

This thesis work is related to the general fields of design-for-manufacturing, process modeling, and continuous improvement and statistical process control. Similar research in manufacturing modeling has been done in [Subramaniam, 1994] in which a manufacturing system is described with a first-order model for a process and with failure mode analysis. Their methodology, applied to aluminum extrusions, deems physical models as beneficial towards evaluating producibility of parts.

Design-for-manufacturing (DFM), as exemplified by [Boothroyd, 1991], relates various manufacturing and assembly techniques to time and cost metrics of the production of parts. While these best-practices serve to reduce costs and to increase efficiency in many manufacturing enterprises, the approaches do not direct efforts to understand the processes involved when the physical mechanics are different than the procedures described by the DFM guidelines.

Statistical process control (SPC) has long been implemented in production facilities to monitor process function and output. Using control charts and time-series analysis, SPC tracks the metrics in the process environment and can assist in identifying when the manufacturing operations are deviating or faulting. However, the information provided by control charts and SPC tools may not directly relate to product quality and process modeling or may be bulk readings not always usable for design engineers. Also, the metrics and parameters to track must be identified *a priori* before installing any monitoring system, which implies that the process is generally understood. This thesis addresses the analysis to be done before SPC can be applied.

Statistics and non-parametric modeling of data have provided a means of quantitatively relating input and output variables without much regard to the physical processes behind the variables. In many cases, these curve-fitting approaches appeal to environments which contain great amounts of data from which numerical models can be found. Splining, surface fitting, and other activities use available data to form mostly continuous functions to provide model equations to predict output.

For small volumes and sparse collections of data, these models can be often crude or unreliable, as the resulting equations can have little relevance to the relations prescribed by the actual occurrences of manufacturing operations. Also, the models can be unrevealing for purposes of understanding the mechanisms involved in a production process. As will be emphasized throughout this thesis, the uncertainty in interpolation and extrapolation and the lack of providing information about the processes and qualitative effects on output significantly limit the use of numerical techniques in manufacturing operation modeling.

2.2 Quality Design Tools and Methods

Of the numerous methods used in quality design, the following have been identified as especially useful and related to this thesis research. Each tool pertains to a particular aspect of the design and redesign processes and evaluation stages. The upcoming sections review the following tools and methods:

- Failure Modes and Effects Analysis
- Fault Trees
- Functional Trees
- Cause-And-Effect Diagrams
- Taguchi's Method & Factorial Design
- Analysis of Variance & Regression

2.2.1 Failure Modes and Effects Analysis

Failure modes and effects analysis, or FMEA, is used to describe qualitative aspects of a product and to guide quantitative corrective measures. Sometimes displayed in tabular form, FMEA tables will include columns of failure modes, effects, and possible causes. A simple FMEA table is shown in Figure 2.1. Typically, FMEA tables will also include columns describing corrective measures or countermeasures, secondary failure modes, parts and components involved, and some general measures describing frequency of occurrence or severity of failure.

Failure Mode	Effect	Causes
tape does not stick	items fall apart	1. dried out 2. not enough adhesive
tape is yellow	obscures background text	1. impure material 2. dirty applicator 3. ... 4. ...

Figure 2.1: A basic FMEA table for adhesive tape

FMEA can also be illustrated by the use of matrices or grids. In this form, multiple causes of failure and product functions or parts are correlated with weightings and correlation scoring. An example FMEA matrix is shown in Figure 2.2. The function with the overall highest percentage priority would then receive the most attention in redesign.

failure modes \ function	function weight	adhesive dries	corrodes over time	gross weight	%
sticks to paper	16	○ 48	● 144		△ 16	208	65
durable	9		○ 27	△ 9		36	11
transparent	9	○ 27	△ 9			36	11
...	4			△ 4	● 36	40	13
						320	100

Figure 2.2: FMEA matrix showing functions and failure modes with weightings, for an adhesive tape example.

Note that in either form, FMEA does not present a quantitative correlation *based upon physical or engineering processes*. The weights and scores assigned in the matrix are non-standardized and while based upon general expectations and experiences of those constructing the matrix, these numbers are user-defined and subject to biases and possibly inappropriate weightings as compared to actual product performances. Even with a more justifiable and robust scoring system, using a baseline and a metric configuration as described in [Otto, 1995], for example, will not ensure that an adequate understanding of failure modes and causes will lead to a quantitative model equation.

In and of themselves, the matrix and table do not indicate any descriptive information that would lead necessarily to a predictive model relating input and output parameters. However, when used in combination with other analysis tools, FMEA can help direct efforts towards learning critical factors involved in constructing a predictive model of manufacturing processes.

2.2.2 Fault Trees

Fault tree analysis (FTA) utilizes a hierarchical illustration of decomposing a product functional fault with not only qualitative subdescriptions of failure, but also allowing identification and association of functional parameters (design and noise variables) with failures. The general form of a fault tree is shown in Figure 2.3.

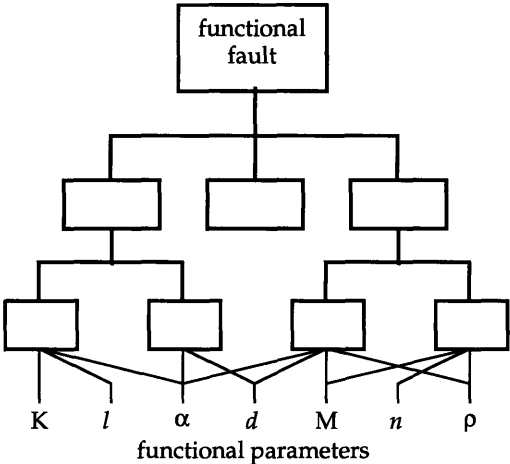


Figure 2.3: Structure of a fault tree

The fault tree, oftentimes implemented along with a form of FMEA, directs engineering efforts to identify critical parameters to production. This relies on adequate

understanding of the process involved, and given that comprehension, there exist many options in experimental design that can result in improved redesign.

The fault tree, like FMEA, is a tool to illustrate and relate failures and manufacturing variables. However, it falls short of providing a quantitative correlation between inputs and outputs. This is not to say that FTA is not useful; fault trees do present design and analysis teams with variables which are deemed important towards improving quality.

2.2.3 Functional Trees

Functional trees, sometimes classified as the tool of reverse fault tree analysis (R-FTA) or the generalized form of the fault tree, relate the expected positive, or successful, operation modes of a product with root causes. The form of a functional tree is shown in Figure 2.4. Note that its structure is similar of a fault tree. It is useful to add the parameter level to a functional tree as is done in a fault tree, with similar results.

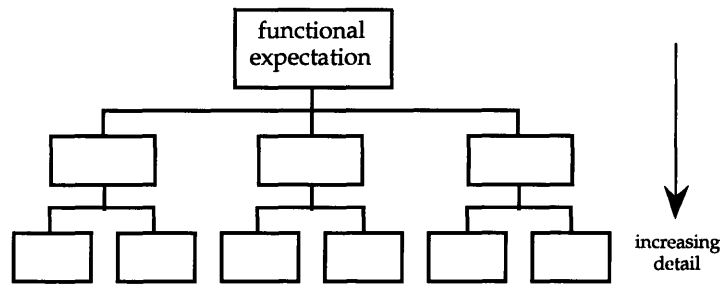


Figure 2.4: Structure of a functional tree

2.2.4 Cause-and-Effect Diagrams

Cause-and-effect diagrams (CE diagrams), also known as *Ishikawa* or *fishbone diagrams*, are relational networks which organize similar information as found in FMEA, FTA and functional trees. CE diagrams are noted as extremely useful in identifying critical parameters as described in [Ishikawa, 1992], [Clausing, 1994] and [Kiemele, 1990].

First formalized by Dr. Ishikawa of the University of Tokyo in the 1940's, the fishbone diagram has developed into a tool for illustrating a trait, function or failure and its corresponding causes. Figure 2.5 presents a typical form of a CE diagram, showing the structure which is reminiscent of a fishbone. As each branch extends from the parent branch, the source of the cause is diagrammed in further detail.

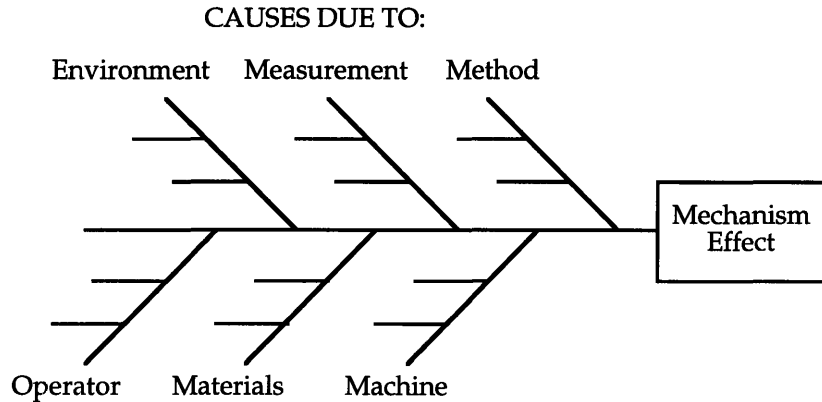


Figure 2.5: A cause-and-effect diagram, branching into six main classifications of causes.

Six categories have been determined to apply to most situations: environment, measurement, method, people, materials and machine. While other classes may be used, these six categories encompass the majority of definable causes of a particular product trait.

A CE diagram can be broken down to more detailed component diagrams, to the point where process and product parameters can be included, similar to fault trees and their relating of critical parameters to a given fault description.

Like the fault trees, CE diagrams allow designers and analysts to focus attention towards understanding the manufacturing system and its quantitative effects on incoming material and resulting properties. Whether determined by brainstorming or other idea-generating methods, cause-and-effect diagrams are useful in correlating qualitative product performance to quantitative parameter identification.

2.2.5 Factorial Design of Experiments

In general, the field of *design of experiments (DOE)* has centered around the use of factorial design. Implemented in *Taguchi's Method* and often called *parameter design*, factorial design aims at determining the most efficient set of experiments to provide the most data about alternative parameter settings at minimal cost or lowest number of experiments.

DOE concepts are extremely valuable towards improving quality of alternate designs. Its main benefit is reducing the number of experiments necessary to indicate better combinations of input variable settings. Simply expressed, and without entering a full discussion of DOE principles, mathematical background and proofs, a factorial

design analysis determines which parameter values tested in a set of experiments will produce an improved product. By implementing sensitivity or signal-to-noise analysis, the value of each parameter which contributes the most improvement in product variance is used in the new design.

Factorial DOE presumes system-relevant parameters have been found and that feasible alternative values have been determined. Output of these experiments do not use nor develop any descriptive equation of the process being tested. Thus, based upon the numerical results, the manufacturing process is not any more understood after the analysis than before even if a more optimal design has been found.

2.2.6 Analysis of Variance & Regression

When studying a process, it is often useful to determine if certain variables affect the output of that process. In this case, a sensitivity analysis can help discern between critical parameters and parameters that only slightly perturb the output. Analysis of Variance (ANOVA) is a technique for decomposing the total variance observed across experiments into the sources of variation. Often used for categorical types of variables, those consisting of a finite number of values or elements, ANOVA can determine how significant variables' changes are towards the changes in the dependent parameter.

By using a statistical test called the *F-test*, two data populations' variances can be compared. Comparing the *F-statistic* with standard threshold values, the significance of the effect of variable a can be inferred. The larger the F-statistic, the higher level of confidence that the effect is real. ANOVA in engineering practice is described in great detail in references such as [Kiemele, 1990] and [John, 1990], and the mathematical derivations will not be included in this thesis.

Multiple regression describes the relationship of a dependent variable with multiple predictor variables in a linear fashion. That is, given a dependent variable y and N independent variables or interactions x_i , multiple regression produces:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_N x_N \quad (2.1)$$

where β_i are coefficients determined by solving:

$$\begin{Bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{Bmatrix} = \begin{bmatrix} 1 & x_{1,1} & \dots & x_{N,1} \\ 1 & x_{1,2} & \dots & x_{N,2} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{1,m} & \dots & x_{N,m} \end{bmatrix} \cdot \begin{Bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_N \end{Bmatrix} \quad (2.2)$$

or:

$$\bar{y} = X \cdot \bar{\beta} \quad (2.3)$$

So the coefficients β_i can be found with:

$$\bar{\beta} = [X^T X]^{-1} X^T \bar{y} \quad (2.4)$$

where X is the matrix of the independent variables and interactions, and \bar{y} is the set of m experiments of the dependent variable y . Multiple regression is useful when trying to model an output variable in terms of a linear relationship of x_i 's. This means that nonlinear relationships cannot be tested directly with a regression fit.

A regression table gives three values that indicate confidence in the analysis. The *correlation coefficient*, specifically the Pearson product correlational coefficient, ranges from -1 to 1 inclusive, or -100% to 100%. 0 indicates a purely random set of data with no correlation to the independent variables. The sign indicates a positive or negative trend. This coefficient is a summary statistic. The *F-ratio*, from an ANOVA of the regression fit to the residuals, compares the predicted percentage of variations to the residual error of the variations. Again, the larger the F-ratio, the better the fit overall. Each *t-ratio* is an indication of the usefulness of each variable or term in a regression fit towards the overall fit. The larger the t-ratio for a regression term, the higher the confidence that the term is significant to the variance in the dependent variable. With each t-ratio is a probability value; the lower the probability, the higher the chance that the regression term, not simply random noise, is causing variation in the output.

Regression is used in this research to test the believability of a model equation with measured data. Using and interpreting regression results for this purpose is described in Section 3.3.5 and 4.3.3.

Chapter 3

A Redesign Methodology Using Manufacturing Operation Modeling

An approach to modeling manufacturing operations for use in product redesign is presented in this chapter. Main concepts are outlined, with each section focusing on a different aspect of the methodology. Section 1 briefly reviews the overall process, while Sections 2 and 3 explain the methodology in increasing quantitative detail. The final three sections address the quality of data and the conclusions drawn from analysis implementing the methodology.

3.1 Methodology Procedure Outline

A manufacturing system is outlined using a flowchart representation. Similarly, the predictive model equation and contributions from manufacturing effects are outlined alongside the system identification. These visual aids are useful in simplifying the information contained in a manufacturing system organization and can be easily changed to accommodate alterations in the system.

3.1.1 Operation-to-Model Flowchart

Manufacturing systems and mathematical transformations have frequently been represented in flowcharts, providing a simple representation of the many functions in a visual fashion. A flowchart is comprised of two main components, the cell and

flowlines. Each *cell* of a flowchart represents a stage of a process that is somehow distinguishable from another process. *Flowlines* are the lines that connect the cells of the flowchart and, with arrows or some other symbol, indicate the direction of material or information flow.

Figure 3.1 illustrates a cell with typical flowline configurations. Input arrives from one or more sources, and output flows from the cell, representing the new state of the inputs after transformation by the cell operation.

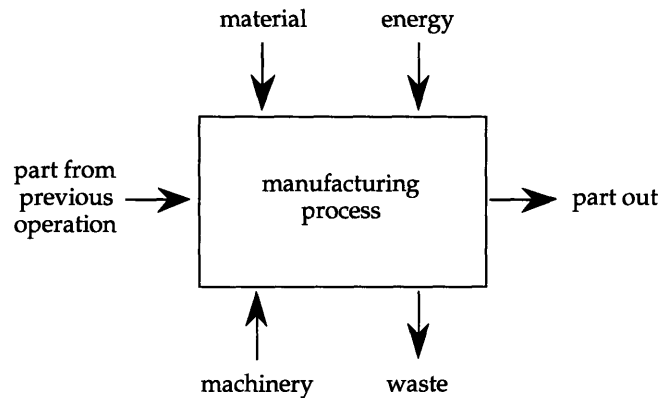


Figure 3.1: Typical flowchart cell with flowlines for a manufacturing operation

In this methodology, the flowchart is concerned with the subdivision of the manufacturing system and the different levels of grouping detail, and with the corresponding developments of the quantitative model. In this vein, a simple operation-to-model flowchart may look like that given in Figure 3.2.

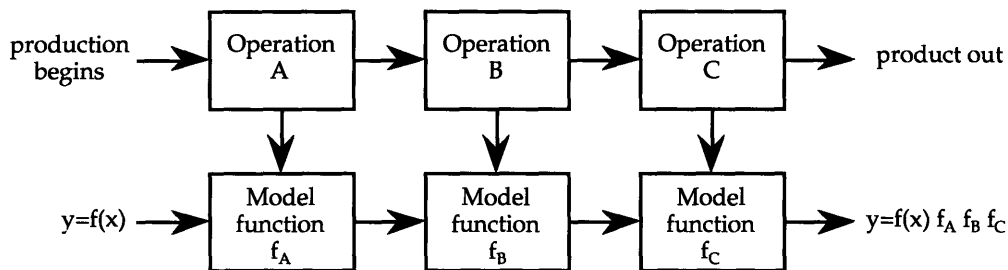


Figure 3.2: Simple operation-to-model flowchart

Figure 3.2 shows a three *operation-model pairs*, or operation cells connected by vertical arrows to model cells. This illustrates a one-to-one correlation between a manufacturing operation and the resulting effect on material as represented in terms of variables of the model equation. An *operation-to-model flowchart* is the assemblage of operation-model pairs.

3.1.2 The Iterative Process

The methodology to improve the understanding of a manufacturing system relies on the analysis of the operation-model pairs. For each pair, a manufacturing operation must be identified, its corresponding model cell formulated, and the overall operation-to-model flowchart amended. These steps are to be conducted in an iterative manner in two ways:

1. *vertical iteration*: the level of detail in each pair should be continually improved and refined, and
2. *horizontal iteration*: other operations in the manufacturing system should be studied in order to develop more operation-model pairs.

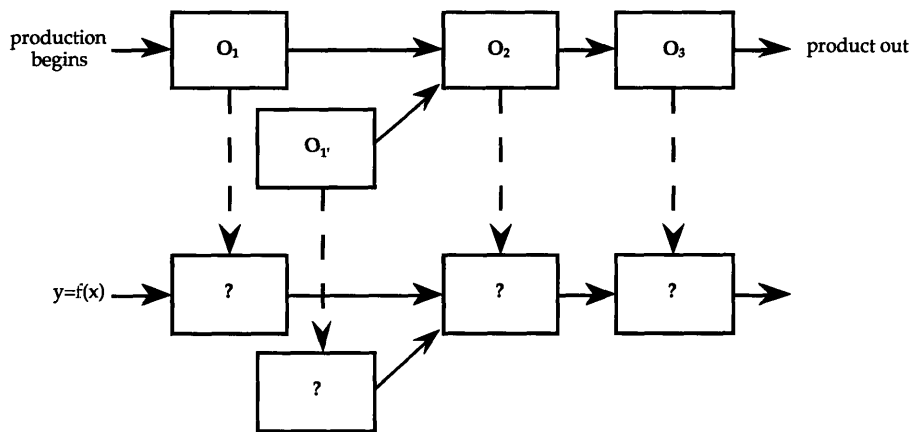


Figure 3.3: Operation-to-model flowchart before any operation-model pair analysis. The model contributions from the operations have not yet been determined, so each model cell is filled with a “?”.

Given a flowchart of the manufacturing system as depicted in Figure 3.3, shown without any operation-model pair analysis, a cycle of the iterative process begins with a manufacturing operation cell. At this point, only the manufacturing operation cell is “filled,” while the model cell is empty, as no quantitative effect has been formulated. This state of the pair is shown in Figure 3.4a, where the operation cell is identified here as O_i . The empty model cell may be shown with no content or with a question mark “?” to indicate that a mechanism effect has yet to be determined². In this thesis, this simple cell-to-cell representation of a manufacturing system is called *single-level division* as each manufacturing subsystem is a single cell, not further broken down into components.

² This is distinct from a model cell of \emptyset (null), which means the process mechanism has no effect on the output.

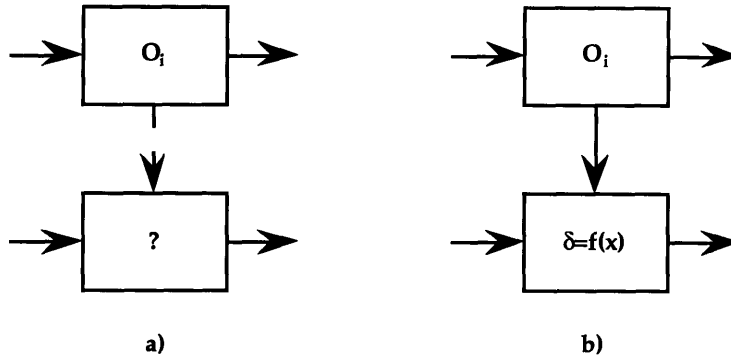


Figure 3.4a: An incomplete operation-model pair without a mechanism effect. The dashed vertical arrow indicates that the model contribution is not known; **b:** An o-m pair with a confirmed mechanism effect in the model cell. Note that the vertical arrow is now solid.

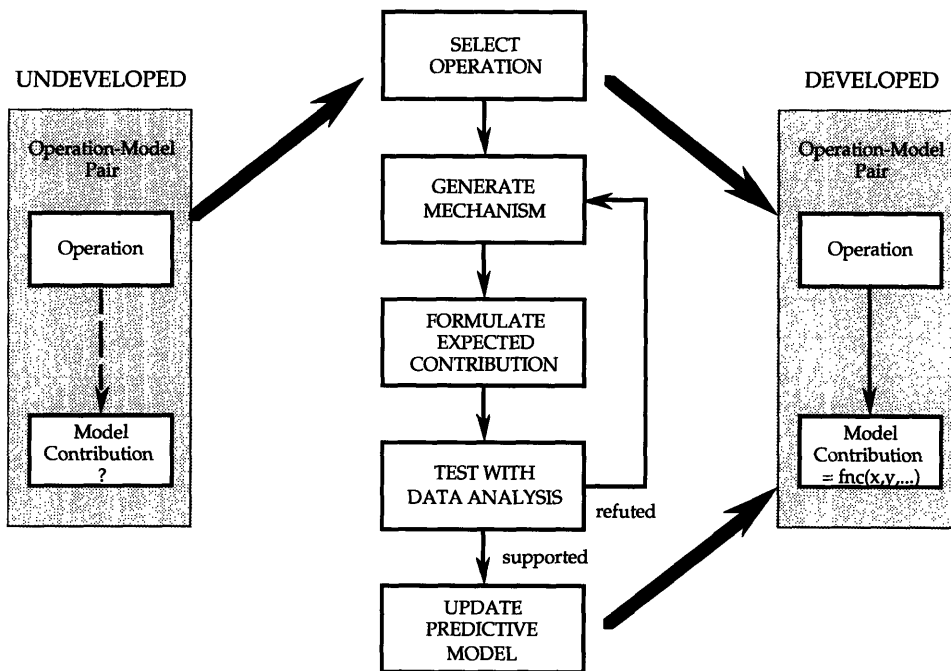


Figure 3.5: The iterative process flowchart of improving the manufacturing model. The methodology begins with a physical or engineering-based explanation, then results in a quantitative contribution.

The iterative process flowchart is shown in Figure 3.5. Beginning with a manufacturing operation, and assuming an operation cell has been appropriately identified and grouped, a qualitative process effect, or *mechanism* effect is pursued. These mechanisms may be identified through brainstorming or other idea generation techniques, and using tools such as fault trees and CE diagrams. The likely quantitative model contribution from the mechanism is then formulated. Upon confirmation by data

analysis, the model cell is filled in, and thus an operation-model pair is complete, as illustrated by Figure 3.4b.

With each iteration in which an operation-model pair is developed, the model flowchart becomes more complete. After a few iterations, the overall operation-to-model flowchart may look like that in Figure 3.6.

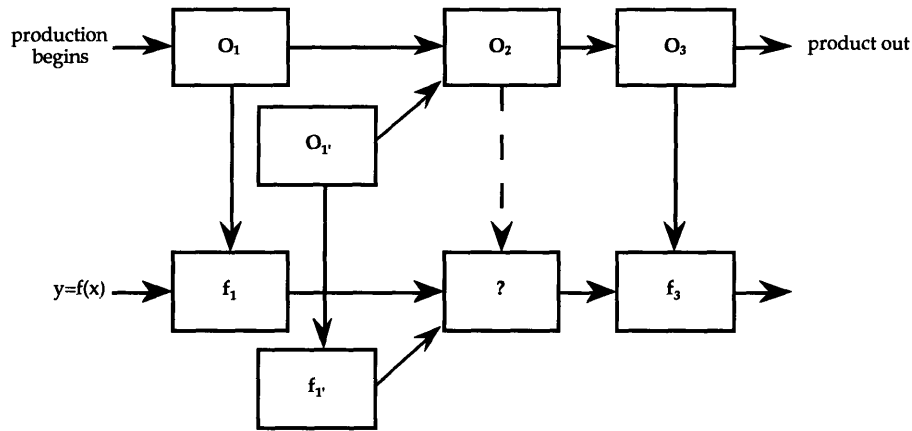


Figure 3.6: Operation-to-model flowchart after a few iterations of operation-model pair analysis. The vertical arrows are now solid, as model contributions have been found.

Following the flowline from the beginning of the flowchart to the end, one can visualize how each operation O_i contributes a quantitative effect f_i to the model equation as the manufacture of the product progresses.

3.1.3 Resulting Information & Implications

In optimal situations, the entire operation-to-model flowchart would consist of complete operation-model pairs. The ideal result of this methodology would be a predictive model including all mechanism effects described by the model cell contributions which mirrors actual production run output.

The more likely case, however, is that some pairs' model cells remain empty. This situation suggests negative implications:

- the manufacturing system is not completely understood,
- the predictive model falls short of describing production output and quality.

From the first statement, empty model cells indicate that the operations represented by those o-m pairs have not yet been correlated with their quantitative effects on the output. This suggests the possibility that the process mechanism is not understood well enough to determine its quantitative effect on the product; the operation flowchart may be further refined so that some subprocesses of an undeveloped o-m pair operation can be developed into their own developed o-m pairs. Generally, empty cells indicate where further analysis must be conducted.

The second implication follows directly from not fully understanding the manufacturing system. For every model cell undeveloped, the predictive model equation will be without a characterizing factor. Consequently, the output and product effects caused by uncorrelated, unmapped process effects will manifest themselves as product variation and failures, and thus lower quality results.

An incomplete operation-to-model flowchart, however, may also be interpreted in a positive manner. Although there will be empty model cells, any developed model cells will improve the model. Understanding one operation and the effect on output is better than not understanding that aspect of the manufacturing system. That is, while a flowchart may be partially empty, it is also a partially developed flowchart that is preferred over a totally undeveloped flowchart.

Thus, the operation-to-model flowchart provides a visual representation of what has been studied and what requires further investigation. It is a type of checklist and management tool that directs resources in an orderly fashion.

3.2 Representing the Manufacturing System

Manufacturing systems typically consist of a large number of individual stages of production, many of which occur simultaneously on different aspects or parts of a product. Proper identification and separation of an entire manufacturing system is essential towards dividing an analysis into portions small enough to be understandable and solvable. Also, improving and managing a manufacturing system require differing amounts of information in process descriptions, so a consistent representation of the operations that can be formed at any level of detail is desired.

3.2.1 Definition of a Manufacturing Operation

Manufacturing attempts to change the form and properties of incoming materials into the desired product configuration. A manufacturing system is composed of multiple

processes and operations, with each individual operation responsible for a specific transformation of the material.

In the interest of analytic simplicity and dividing a manufacturing system into comprehensible units, this research considers a manufacturing operation as an action or a group of actions which is responsible for a particular trait or transformation of a property.

While this definition leaves much room for interpretation, its main connotation involves reducing a complex system into a number of processes, with each process dominant in its own aspect of the manufacturing line. This concept assumes approximate independence of one process from another; to first-order, one operation's effect on material is largely unaffected by subsequent operations. This does not imply, however, that subsequent operations do not change the result of a previous operation. In fact, this situation is seldom true. It does imply, though, that subsequent operations affect previous transformations in a regular, scaleable and functional fashion.

This introduces the concepts of *primary function* and *secondary effects*. An operation's primary function is the intended purpose of that particular process. The designer of the manufacturing system chose an operation to perform this function. Therefore, the primary function of every operation is known, or was known at the time of the system design. The corollary is to say the operation is necessary to the manufacturing system, and that without the operation or an equivalent operation, the product would be without the effects of the primary function.

Secondary effects are the undesired or unknown alterations to material and properties that were not intended by the inclusion of the operation into the manufacturing system. These effects may also be known effects that were initially found to be of small enough magnitude for the original manufacturing system requirements, but which have become nonnegligible as the production line and its product progressed and evolved. The secondary effects in this case may have been forgotten or mistakenly left out of the manufacturing model, or incorrectly considered insignificant, as the system developed in later periods of use. It is the tracking and understanding of these secondary effects, caused by mechanisms, which is central to the product and process redesign and improvement methodology.

3.2.2 Subdivision of Operations

Grouping of subsystems and their component processes allows for visual comparison of steps in a manufacturing system. In more abstract review of an entire system, only the

main divisions of subsystems are relevant, while in more detailed applications, how each operation within subsystems compares with other processes is necessary information. Thus, operations must be grouped in varying levels of detail.

As the operation-to-model flowchart is developed, it may become apparent that some operations in the operation flowchart must be further divided. For example, complex operations involving multiple steps may warrant such subdivision into what is referred to as *real* components. In other cases, an operation may be *virtually* divided, in that, say, while only one physical step occurs, the operation may be represented as a superposition of separate effects, all happening at the same time in the single operation.

Similarly, as each real or virtual subdivision operation is identified and represented, a corresponding model subdivision should exist to maintain the one-to-one balanced pair.

In terms of visual representation with cells, as was done before with single-level division and depicted in Figure 3.7a, *multi-level division* takes on a structure similar to that shown in Figure 3.7b.

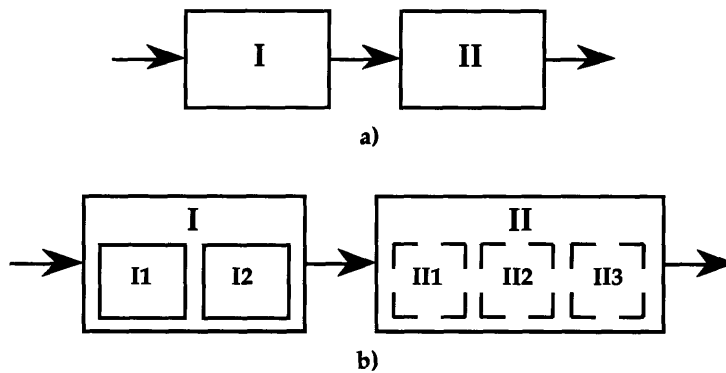


Figure 3.7a: Single-level division of cells for either operation flowcharts or model flowcharts; **b:** Two-level division of cells. Cell I includes real components, while cell II consists of virtual components.

As can be seen in Figure 3.7a and 3.7b, the larger cells I and II are the main components in the flowchart. In Figure 3.7b, cell I is further subdivided into smaller cells I1 and I2 with solid boundaries representing separate real components, while in cell II, smaller cells II1, II2 and II3 are shown with dashed lines to represent virtual components.

For a given complex operation, more than two levels of subdivision may be required. In this multi-level division situation, a cell is simply shown with its components inside its own boundary.

In this representation, it is simple to discern which operations in a manufacturing system are complex and which are simple. Also, the number of levels in one subsystem compared to another indicates where much attention has already been focused. Single-level cells in a multi-level flowchart would represent operations that might contain great potential for further studies and improvement merely because they have yet to be considered in as much detail as for multi-level cell operations.

3.2.3 Serial & Parallel Process Flow

In Figures 3.2 and 3.7, *serial* process flow has been shown. Serial flow denotes that the main material and information is passed sequentially from one operation to another.

In real manufacturing systems, material that results in a finished product often originates from separate lines of production. One product part is manufactured in one factory line, while another part is made in another before the two parts are processed together to form the final product. This disjointed flow is termed *parallel flow*.

In the cell representation of the manufacturing system, parallel flow is shown as separate serial flowchart segments that join or separate at some point in the flowchart. Two simple parallel processes joining at an intermediate cell in a manufacturing system representation is shown in Figure 3.8a. In this case, the parallel flow is *converging*, where the two parallel flowchart segments meet in the direction of the flow. In Figure 3.8b, the flow is *diverging*, where some part of the product is processed in one parallel line, and another part of the product is done on another.

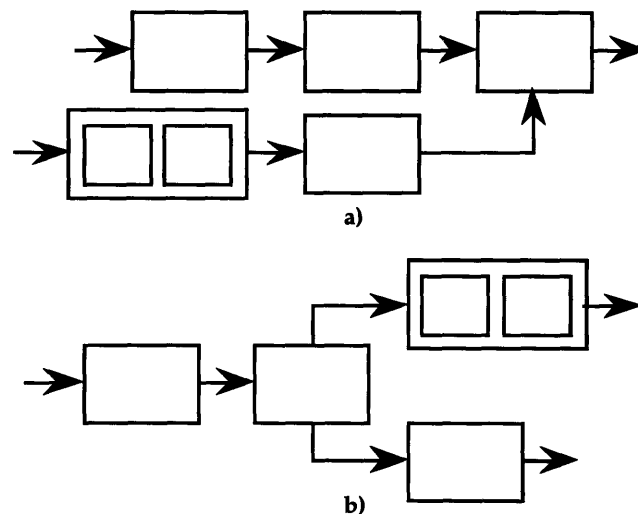


Figure 3.8a: Converging parallel flow in manufacturing process modeling; **b:** Diverging parallel flow

Recognizing serial and parallel flow in a manufacturing system and developing those flowchart segments is important towards identifying previously neglected sources of error in the product. It is possible that incoming material has been initially represented as simple constant input into a cell, whereas the parallel processes responsible for that material includes many sources of variation not obvious without the aid of the more complete flowchart representation.

Again, serial and parallel flow representation is equally applicable to model flowcharts as it is for operation flowcharts. This maintains the operation-model pair utility required for the iterative process analysis.

3.3 Modeling Manufacturing Operations

Given a representation of a manufacturing system, the next step in the methodology is to quantify manufacturing operations. Referring back to Figure 3.2, each secondary effect of an operation has a quantitative contribution to the predictive model equation formed by the primary effects contributions. Thus, forming these contribution equations and confirming them with product data is essential towards improving production quality in redesign.

3.3.1 Variable Set Selection

Products and processes can be described by multiple levels of variables, each level consisting of varying amount of detail. In lower levels, elementary variables can be used to describe a process or product, while in higher levels, fewer variables make up that set of variables used to describe a product or process. More elementary variables, like pressure and machine speeds, for example, tend to be only measurable at the time of production, or during a process. Often, these are called process variables. Higher levels of variables typically consist of product variables, those which are measurable after production and can be repeatably measured given nondestructive or nonintrusive measuring schemes, and design variables, the desired output of a process. Design variables are the ideal values and targets for the product variables.

For this methodology, an appropriate variable set is required. Ideally, a comprehensive set of process and product variables would be acceptable. "Comprehensive" suggests that all of the critical parameters that affect a product's quality are *known*, *measurable* and *adjustable*. Also, the input and output variables

should be *piece-part correlated* with parts, as opposed to batch-averaged or uncorrelated variables with products.

However, a comprehensive set of variables for a quantitative model is generally not possible due to the existence of unidentified variables, constants and noise variables. It is important, though, to strive for the best variable set by iteratively developing and understanding system parameters, and to pursue the characteristics of a comprehensive set.

The first characteristic of an ideal comprehensive set, that the parameters are known, is not frequently achieved in industry or research. By knowing the variables affecting a process, changes in the output of that process can be achieved by making changes in the input, and this can occur only if those input parameters have been identified. The current practices of DOE have been developed to determine which variables of a subset of process settings are more critical than others, but make no attempt to direct manufacturers towards finding all important variables assuming that some have not yet been determined. Processes are often so complex that there are likely some variables that have not yet been identified.

The second trait of the comprehensive variable set is that the parameters are measurable. Even if a set of variables are known to contribute to a predictive model of production, these variables may not be easily measured. Again, this difficulty may be due to technical and non-technical issues. In either case, there is less benefit in claiming a variable is important to a model equation if it cannot be measured consistently or accurately. Being able to measure the parameters allows comparison of causes and effects of product quality and performance.

A third characteristic of a comprehensive variable set is that the parameters are adjustable. This means that if a different value of the variable is desired, that parameter must be conformant to change and realizable. Thus, if the desired value of a parameter is one that cannot be achieved because the variable is essentially constant, that variable would not be as useful as an equivalent variable that can be adjusted. A parametric model of the manufacturing process depends on adjusting input variables to provide a predictable and expected change in output.

It may be necessary to use a combination of product and process variables. End-of-line product variables, by nature, can be piece-part correlated, while process variables must be measured during production and associated with the part as it flows through the manufacturing system. Product variables, describing the final state of a product and its properties, are fewer in number and generally easier to measure. Process variables, however, are not completely neglected when using a variable set of only

product variables. Process variables and their values are quite important in determining the model contributions of secondary effects. It is the uncertainty and incomplete understanding of processes and corresponding parameters, not necessarily the negligence of them, that limits the use of process variables.

3.3.2 First-Order Base Equation

Given an appropriate variable set, a first-order base equation, or set of base equations, must be formulated in terms of variables in that set. The base equation provides an initial quantitative model, the output being what the manufacturing system was originally designed to accomplish but now does not satisfy company requirements.

The primary functions of the manufacturing operation are known and were intended. Ideally, their quantitative effects should similarly be quantitatively known. If indeed known, then the base equation is simply made up of these constituent relations. It is desirable to form a base equation from first-principles and established engineering and physical knowledge, as these principles have been repeatedly supported and confirmed with carefully conducted experiments. The variables found in these representations are necessarily components of the variable set chosen for the overall manufacturing system.

If the model is partially or wholly based on empirical relations, this model is also useful, although the experimental nature of the equations tends not to be as generalizable for large ranges of input and output requirements. If empirical relationships are the best quantifiers available, then the base equation must be formed from these approximations. However, beginning with a statistical and numerical equation risks the incorporation of secondary effects into a base model that a manufacturing enterprise wants to identify and correct.

3.3.3 Mechanism Identification

While the primary functions of the manufacturing system, and consequently the quantitative effects of the intended processes, are generally understood from the outset, secondary effects are not known from the beginning. As this methodology directs, finding causes of base equation perturbations is key to recognizing and improving production constraints, so possible sources of variation from the base equation must be identified and analyzed. For each mechanism generated that might be a source of a modification to the predictive equation, either support or refute of the mechanism is

useful to gain further understanding of what is and is not occurring in the manufacturing process to the product.

Standard tools, including those described in Chapter 2, can be implemented to generate mechanisms for process steps in the manufacturing system. CE diagrams, fault trees, FMEA and brainstorming techniques are particularly useful. The important commonality in all of these methods is identifying possible sources not accounted for in the base equation representation of the system. This means that particular components of the machinery, tooling, materials and similar inputs to the manufacturing system need to be reviewed.

The analyst must understand the given process at hand in sufficient detail to identify second-order effects. “What if” scenarios should be developed and, as in brainstorming techniques of idea generation, should not be immediately discounted without further consideration. Previous experience with the manufacturing system will be valuable in determining feasible targets for improvements, yet personal biases not based on fact or real evidence will hinder uncovering problematic areas in production. The purpose of mechanism identification is to find *possible* sources of secondary effects previously ignored or overlooked. Evaluation of these possibilities is a forthcoming step.

Mechanisms are likely to include process and material considerations. Hence, corresponding process and material parameters should be available, as these will become important in the next steps of the methodology. Cause-and-effect diagrams and fault trees are particularly useful in this step in that they help analysts consider the many inputs to an operation in an organized fashion, and well constructed CE diagrams and fault trees will have associated with each fault a set of variables deemed important to that root. A subtle difference in implementing these standard evaluation tools is that in this implementation, the breakdown of an operation results in possible sources of secondary effects, not confirmed sources of variation or failure.

Each identified mechanism should be documented in a consistent or standard form. General categories or classifications of sets of mechanisms will likely help in organization as is done in fault trees and FMEA analysis. If applicable, location of proposed effect should be indicated, by illustration or detailed description.

Similar documentation practice should be followed in coordination with the operation-to-model flowchart. If the categorical grouping of mechanisms represents subgrouping of a manufacturing system operation not yet illustrated by cell division on the flowchart, then it may be helpful to perform that subgrouping division.

3.3.4 Form of Mechanism Contribution

Once a mechanism has been identified, the following issues must be resolved:

1. Does the mechanism affect all or only a selection of products for a range of material and process inputs?
2. How would the effect be described by an equation using the chosen variable set?
3. What is the specific behavior of the effect on the product?
4. How do the material and process parameters enter into the description of the secondary effect?

Some mechanisms may only affect some products rather than all. This may be simply due to different materials for different production runs, for example, so a mechanism specific to a particular material will only appear in the output using that material. Other mechanisms, perhaps a machine-related effect, will occur regardless of incoming material. Thus it is important from the outset to determine what portion of the product sampling is to be considered for further analysis.

As the parameters in the variable set vary, the output will likely vary also. For example, if the chosen variable set consists of a number of product and design variables, then for each value of a parameter, there may be some manifestation of the secondary effect in the output. This manifestation is to be predicted and derived using the variable set.

Because the variable set may be comprised of variables which behave in similar ways for multiple mechanisms, any characteristics that differentiate one effect's trends from another should be determined. Are there particular characteristics of the proposed model contribution in magnitude and sign? Suppose two mechanisms are found to be proportional to the same variable in the variable set. If one mechanism's model contribution is derived to be an order of magnitude larger than the other effect's contribution, that discerning feature should be noted. Similarly, the sign of the relationship to the variable may be important.

As the mechanism contribution is determined to be related to some of the elements of the variable set, the coefficients of the terms will be dependent upon other influences. In each operation, the material and process variables cause these differences, and understanding the material transformation process and the underlying physics or engineering concepts behind them may lead to a descriptive equation outright. However, often there are no applicable models relating elementary variables to output variables, so

this outcome is not common. More typical is the recognition of qualitative trends related to material and process parameters. First-order and perhaps second-order trends may be determinable; this is analogous to knowing the general slope and the curvature of a trend.

Since there is uncertainty in knowing how exactly the material and process variables relate to the output, the quantitative trends can only be approximated. Thus, an appropriate mathematical equation that reasonably demonstrates the desired trend is acceptable. For example, in some cases, logarithmic and asymptotic proportionality may be equivalent to an inverse relationship or another simple series expansion. Whether one form is better versus another depends on the characteristics of the trend and how much is known about the manufacturing operation. The more is known, the more critical the selection of a representative model contribution equation.

As will be discussed in the next section, some forms of mechanism contribution may be easier to test than other equivalent equations.

3.3.5 Support or Refute of Mechanism

Now that a function describing the expected secondary effect on output has been formulated, it must be tested with existing data of real product measurements. Referring back to Figure 3.5, if a mechanism's effect is supported, then the model contribution can be integrated into the predictive equation. If the mechanism is refuted by the data, then the secondary effect is not significant or is not the dominant effect in the manufacturing operation selected for investigation.

Using Regression Analysis

Regression analysis, as briefed in Section 2.1.6, is a commonly used statistical tool that can reveal how an output variable relates to one or more proposed terms in a linear fashion. Since regression is based upon linear functions, it is limited to testing data with equations that can somehow be transformed into a summation of individual terms. However, with some manipulation and combination of variables, many equations can be represented in a linear order, and thus can be analyzed with regression tools.³ For example, consider the relation:

$$y = \frac{u^\alpha v^\beta}{w^\gamma} \quad (3.1)$$

With some manipulation, this can be written as:

³ A nonlinear equation poses a more difficult task for analysis, and this issue is not addressed at this time.

$$\ln y = \alpha \ln u + \beta \ln v - \gamma \ln w \quad (3.2)$$

Thus, by transforming variables into logarithms of themselves, a regression may be performed properly on this particular sample equation.

If the initial formula of the mechanism contribution is not in a linear format, then it needs to be rewritten to accommodate the regression analysis. Otherwise, it may be possible to find an equivalent equation that can be written in linear form.

Since this method is concerned with secondary effects, or deviance from a base equation, it may be more appropriate to test a nondimensional form of the data. This can be achieved by normalizing the measured data with the first-order base equation or by constructing a variable of the measured value divided by the predicted value.⁴ This latter variable will be termed as percentage variation.

By removing the first-order primary function effect from the data, the “leftover” containing secondary effects and noise remain, as noted in Section 1.2.2. Thus, by analyzing the variation from target or the percentage variation, a secondary effect contribution can add onto the predictive equation as a correction factor, a nondimensional adjustment that represents a scaling of the base equation. These factors may be heavily dependent on material and process variables as well as the design or product parameters in the variable set. Such correction factors $F=fnc(\{x_i\})$ would amend the predictive model as such:

$$\hat{y} = fnc(\bar{x}) \cdot F_a \cdot F_b \cdot \dots \quad (3.3)$$

Interpreting Regression Results

When using regression analysis for linear relationships, interpretation of regression tables should be carefully related to the mechanism contribution formulation. The variables in the regression table will have associated with them coefficients, t-ratios and probability values, and the entire regression has an r-squared correlation value and the standard error of the dependent metric.

When used to evaluate overall adherence of data to a modified predictive model, and in comparing two models with the same set of data, the r-squared correlation is a fair indicator. While the correlation coefficient value usually has a monotonic behavior with improved results, the value itself is dependent upon the size of the design window domain, the subset of data used in the analysis. This issue is discussed in [Kiemele, 1990] and is a reason the correlation value is of limited use in practice.

⁴ Using the target value for comparison carries with it some nonoptimal implications. Those issues have been discussed in papers such as [Hunter, 1985], but nonetheless serve as one way to compare data with theoretical values.

A better quantity to monitor is the standard error value, and unlike the r-squared coefficient, its interpretation is consistent across the size of the domain. Its value can be meaningful to the design and process engineering analyzing the operations, as it measures the standard error of the output, the sigma value used in “Three Sigma” or “Six Sigma” quality pursuits.

When evaluating a mechanism, the probability values of the t-tests prove useful as confidence level indicators. In general, the lower the probability value, the better the fit of the linear term to the data. By comparing the resulting probability values with a pre-defined confidence value or threshold, a coefficient and the regression term can be evaluated for acceptance and believability. The threshold value for the probabilities should be chosen consistently for all mechanism analyses.

The coefficient for the variable must also be considered in deciding whether the mechanism is supported. As mentioned in Section 3.3.4, a mechanism will have an anticipated order of magnitude and sign, so these expectations must be reflected in the regression analysis. A side benefit of a regression fit conforming to the expected general form of a mechanism but not satisfying magnitude and sign expectations is that the analyst has a trend in the data that must have a corresponding mechanism to explain it.

A note of caution, however, when interpreting correlations. It is conceivable that regression analysis will give positive results. If possible, datapoints should be compared with constituent variables in graphical form to ensure that the regression fit accurately identified a true correlation trend. Variable confoundedness might also cause this effect.

Given all of the above positive indications that a mechanism’s model contribution is well correlated with the actual measured product data, the selected mechanism is thus supported, and thus the secondary effect is considered present and active in the manufacturing operation. Only one negative indication refutes the mechanism.

Supported mechanisms lead to the development of the operation-model pair, as outlined in Section 3.1.2. If, with additional measurements and knowledge about the system, the secondary effect is not further supported, careful reevaluation must be done of the original mechanism.

Once a secondary effect has been confirmed, the iterative process may continue with a vertical selection (the particular operation can be additionally investigated) or horizontal selection (another operation may be studied).

3.4 Conclusion Scenarios

When can analysis stop? In real-world settings, depletion of resources and the approach of deadlines may prematurely halt the research process before technical limitations arise. However, stopping criteria must be established to provide definite goals and benchmarks. These guidelines also help ensure that valuable resources are not spent on pursuits that are of low utility to the company or that cannot be achieved without additional information. Adding the stopping criteria considerations into the methodology results in a more complete iterative process chart, given in Figure 3.9, which also includes an experimentation step.

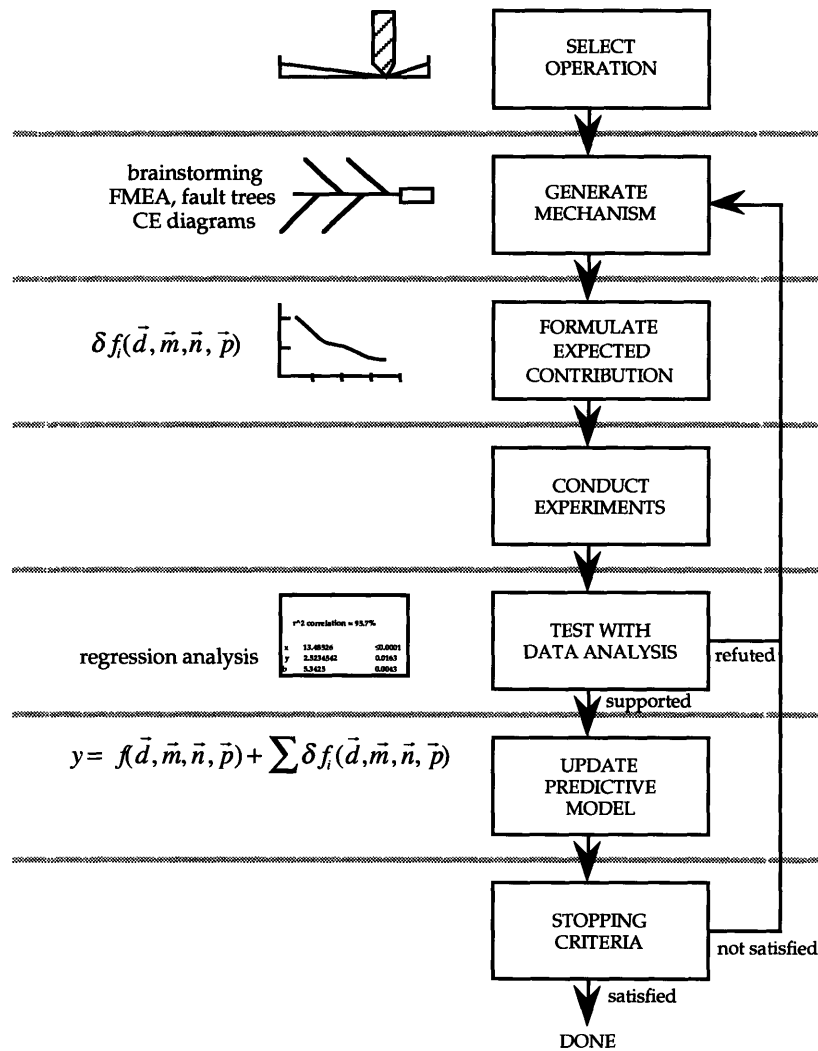


Figure 3.9: The iterative process flowchart including stopping criteria considerations

These termination criteria consider the practical application of analysis towards product development. Although the philosophy of continuous improvement suggests that the iterative process never cease, companies today still must make trade-offs between research and production. Thus, the following conditions are possible reasons that analysis may be halted.

3.4.1 Removal of Discernible Trends

In the ideal case, the removal of all trends is the ultimate achievement in modeling the manufacturing system. However, the practical interpretation of this criterion is that all *discernible* trends have been found and accounted for. This status is achieved when further analysis fails to support any conceivable mechanism proposed after extensive effort. Further, the performance metric errors are directly related to the constitutive component errors via Equation (1.1). This implies that the remaining variation from the target value is caused only from true noise in the system, not from an inaccurate model describing the operations.

Additional measurements on products will enlarge the dataset and possibly expose trends not previously encountered, and mechanisms proposed for the original data should be reevaluated for this larger collection. It is foreseeable that some once-supported mechanisms are invalidated, while once-refuted mechanisms find support with additional information. Reevaluation requires referring back to the analysis done prior, and thus proper documentation is desired, especially if different analysts are testing the larger dataset.

Unfortunately, reaching this condition does not guarantee that the manufacturing process are under control or acceptable. It may, however, suggest that improvement efforts may be better used to control variation or decrease the noise in the system in particular.

3.4.2 Realization of Specifications

Usually a factory or company has established specifications for its product's performance. Having applied this methodology to improve the predictive model and thus decreasing variation as outlined in Sections 1.2.2 and 1.2.3, the product quality may improve substantially enough to meet these specifications.

Again, this is only a temporary condition for halting analysis, a short-term solution. More demanding product performance may be required in the future, thus requiring more improvement in manufacturing. Assuming that there are additional

mechanisms to be evaluated and model contributions to be found, or that the data still contains discernible trends, the raising of product standards directs attention back to the unresolved mechanisms not yet tested. This contingency also supports why documentation is desirable even after specifications have been achieved.

3.4.3 Variable Confoundedness

Recall that in real working environments there may have been limitations in data quality, that no experiment was ever conducted to gather data or that the experiment done was not well-designed. The design and manufacturing teams may have simply not known what parameters were important when deciding what to measure.

Nonoptimal DOE or limited-resource experiments may suffer from *variable confoundedness*. Basically, this means that two variables that are independent in nature have been varied in tandem. Or, given one independent variable's value, a second independent variable's value is known *a priori*. For example, suppose that two variables describe different geometric measurements on a part. *Value-to-value confoundedness* occurs if one variable's value in the experiment always occurs with the same value of another variable. Knowing one parameter means another is known.

Confoundedness also occurs when knowing one variable's value is associated with a small range of values of another variable, with the ranges of values of the second variable mostly distinct and not overlapping with each other. In other words, rather than there being a value-to-value confoundedness, there exists a *value-to-range* or *range-to-range confoundedness*.

In analysis, then, an apparent trend that is postulated and supported by a regression may be false if the term variables are confounded. For example, suppose a mechanism may predict a model contribution proportional to x , and statistical analysis supports the proposed formulation. However, if x is confounded with another variable w by the DOE construction, it is not justifiable to accept the mechanism as a secondary effect to the manufacturing system description because the data trend may be actually be caused by a mechanism contribution dependent on w . Without data from an unfounded experiment or production runs, it is not advisable to implement a modified model using contributions from confounded data.

A solution to variable confoundedness is to perform another experiment or set of tests unlinking the two or more variables and randomizing their values with respect to one another. This additional set of experiments may be an unwanted demand on time and resources, but if resolving a trend in a confounded variable is valuable to the

manufacturing system model, then correcting the situation can be deemed necessary. In cases where justification for more experiments is required by management, the identification of confounded variables shows that more research should be approved.

3.5 Benefits of the Methodology

Since the research is rooted in actual manufacturing applications, the methodology has benefits not generally found in other techniques. The iterative process to develop the qualitative and quantitative models for production incorporates both management concerns and technical issues, and consequently is beneficial in both realms.

3.5.1 Interpolation and Extrapolation

Methodologies that employ surface-fitting, numerical and statistical modeling without a physical mechanism basis suffer from their shortcomings in interpolation and extrapolation potential. In some techniques, any high-order function or polynomial that fits the data provided is satisfactory. However, when considering new product options, with parameter values different from those upon which the numerical equations were calculated, interpolation accuracy is questionable. Extrapolation beyond the extents of surface-fit endpoints are even more suspect than interpolation, as there is little guarantee that the model captures the physical effects in these untested domains.

As discussed previously, beginning with numerical fits and then finding a physical process that might explain the data may work well in some applications, but often those equations are difficult to interpret or transform into meaningful manufacturing effects.

Since this methodology begins with a possible manufacturing mechanism and then tests with data its presence, the resulting model reflects actual processes, and thus intermediate values to those measured are more valid and believable than those obtained with equation-first-mechanism-later approaches. Similarly in extrapolation, predicting output at input values not contained in the dataset is more dependable.

3.5.2 DOE Identification

An optimal set of experiments may not have been run for a number of reasons: management needs justification for experiments before approval, so no planned experiment was ever conducted; non-technical issues required a smaller and less

informative test set to be pursued; the critical or important variables to the manufacturing system were not known.

By attempting to use available data and searching for secondary effects, any trends uncovered and critical parameters determined can be used to justify future experiments. Any variables which were confounded but show some correctable trends can be subsequently submitted for inclusion into an unconfounded DOE. By following the methodology and paying attention to the conclusion scenarios, confounded variables can be identified. Investigating sources of error in the predictive model may also lead to the discovery of important parameters not previously known.

3.5.3 Critical Operation Identification

Once some operation-model pairs have been developed, it can be determined which model contributions are most significant to the predictive model. Recalling Section 1.2.3 and Equation (1.1), output variation is dependent upon both the accuracy of the model equation and the variation in the input parameters. Thus, secondary effects can have differing influence on the model, and thus varying influence on the variation of product characteristics.

This can be used as a management tool to direct resources and efforts to meet specification requirements. If one manufacturing operation's model contribution is an order of magnitude of greater than other operations, then it is desirable to pursue improvement in that one section of manufacturing because that operation is where the most improvement can be gained.⁵

3.5.4 Factory & Manufacturing Understanding

Numerical methods do little to direct or encourage the study of the physics or engineering, and therefore its solutions are not necessarily accompanied by insights into what is or is not really happening to the materials throughout production.

In this methodology, scientific reasoning is at the heart of the process so there is always an impetus to understand the actual processes involved in the manufacturing system. For the company personnel in charge of overseeing the system, the qualitative modeling of the operations simplifies the representation of a complex and otherwise incomprehensible series of manufacturing stages. For the team assigned to an operation or subset of the system, understanding processes in greater detail and pinpointing

⁵ The idea of error budgeting is not new, as demonstrated by implementations described in [Slocum, 1992], for example.

sources of secondary effects enhances its ability to operate and improve production at the machine level. With experience, the methodical and logical search and resolution improves the problem-solving capabilities of the firm.

3.5.5 Division of Work & Responsibilities

Once a basic qualitative manufacturing system model is established, project work teams can work independently of one another. This allows great flexibility in scheduling and resource allocation, as one team is not directly constrained by another. Using the operation-to-model flowchart as an indicator of progress, managers can determine where to shift attention.

The modeling structure can be hierarchically applied to the multiple teams in real design-and-manufacturing enterprises. Again, since the methodology has been developed based upon actual working organization of companies, the considerable independence among project teams is advantageous. The modeling procedures recognizes that teams may be separated by geographical, technological and scheduling divisions and thus accommodates this separation.

3.5.6 Expandability of System Model

The modularity of the system model as represented by the operation-model pairs in the flowchart suggests the relative ease of considering and executing changes to the manufacturing system. Suppose that an operation evaluated and expressed as a developed operation-model pair is found to introduce unacceptable secondary effects and can be improved by another operation, using a different machine or component in the process. Or suppose an additional operation is to be inserted in the manufacturing sequence. Both events can be accommodated by the methodology since the operation-to-model flowchart is based upon the actual operations in a system. Operation replacement and insertion is diagrammed in Figure 3.10.

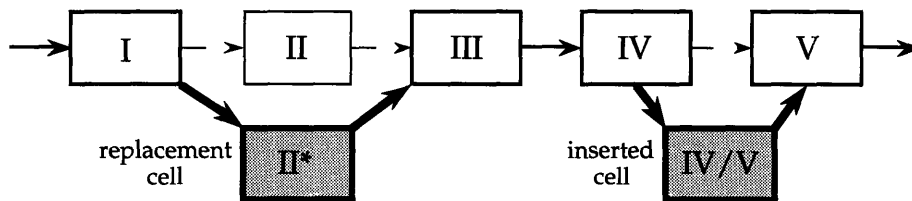


Figure 3.10: Operation replacement and insertion into the system model. Cell II* replaces Cell II, and Cell IV/V is inserted between Cell IV and Cell V.

3.6 Limitations of the Methodology

As this methodology is built upon real situations in industry and suited for actual application, it is consequently limited by constraints in a company and the amount of unknowns in process understanding therein. Because there are few ideal cases of operation modeling, however, the practical basis of this methodology gives it potential for maximum benefit to a real system, and this consideration should be kept in mind when evaluating the utility of this research.

3.6.1 Knowledge Requirements

The iterative process requires understanding the finer details of operations in order to identify possible mechanisms. Thus, this methodology does not replace the need for well-qualified personnel in the technical fields, nor does it eliminate analysis or research in the field. Unlike some methods which allow for uninformed or unskilled employees to conduct numerical processing, typical in more statistical approaches to modeling, this methodology necessitates that the participants in project teams be analysts and have technical background and qualifications.

Managers must also have background in technology and understand the product performance as a whole. Without a solid knowledge of design and manufacturing concepts, a supervisor of the system modeling process will be unable to integrate the results of project teams and their quantitative modeling results.

3.6.2 Uncertainty

Uncertainty or, specifically in this methodology, incomplete knowledge limits the quality of product performance as an exact quantitative model is difficult to achieve. The unknown effects and variables in manufacturing plus the shortcomings in experimentation limit how much improvement can result from application of this research.

Variable confoundedness and inherent noise in the system also cause potential improvements to be obstructed from confirmation or identification. The nature of the scientific method and the difficulty of completely proving the existence of a secondary effect during a operation lends conservatism to this work.

3.6.3 Independence of Effects

One of the assumptions of this work cited the approximate independence of one operation from another. As mentioned in Section 3.2.1, secondary effects' transformations were taken to affect previous operations in regular, scaleable and functional fashions. Thus, mechanisms which affect previous operations nonlinearly or nonfunctionally are more difficult to accurately represent.

However, given that most mechanisms are understood only partially and can only be supported by nonoptimal datasets that include uncertainty, it is conceivable that the form of the quantitative modification of the predictive model as suggested in this methodology is still valid.

Chapter 4

A Methodology Case-Study: Resistance Analysis of LTCC Circuits

The following case-study was conducted in parallel with the development of the methodology presented in Chapter 3. It is clear that evaluating a real product with actual technical and nontechnical issues improves upon the applicability of the method to other real cases.

In Section 1, an overview of the product and important issues is given. An example of modeling without applying this thesis' principles is discussed in Section 2, contrasted by Section 3, the results of analysis using the methodology. Conclusions and future work specific to this case-study are found in Section 4.

Due to the sensitive nature of the product and performance, company names and certain identities and sources of information have been omitted to maintain proprietary rights and confidentiality. The values given, however, are the actual results from analysis. Also, because of the large amounts of data and graphs used in this research, only information needed to illustrate the methodology are included.

4.1 Project Overview

The technology of the low-temperature co-fired ceramic (LTCC) circuit is briefly discussed in this section, which also includes a review of the research project and the manufacturing environment of the actual product samples.

4.1.1 Background of LTCC Technology

LTCC circuits⁶ are one classification of hybrid circuits. Hybrid circuits generally consist of components printed or deposited on a substrate of insulating material, and can host semiconductors and other parts in an assembly. The circuits can then be packaged and connected to external devices and wireboards. An LTCC circuit is shown in Figure 4.1.

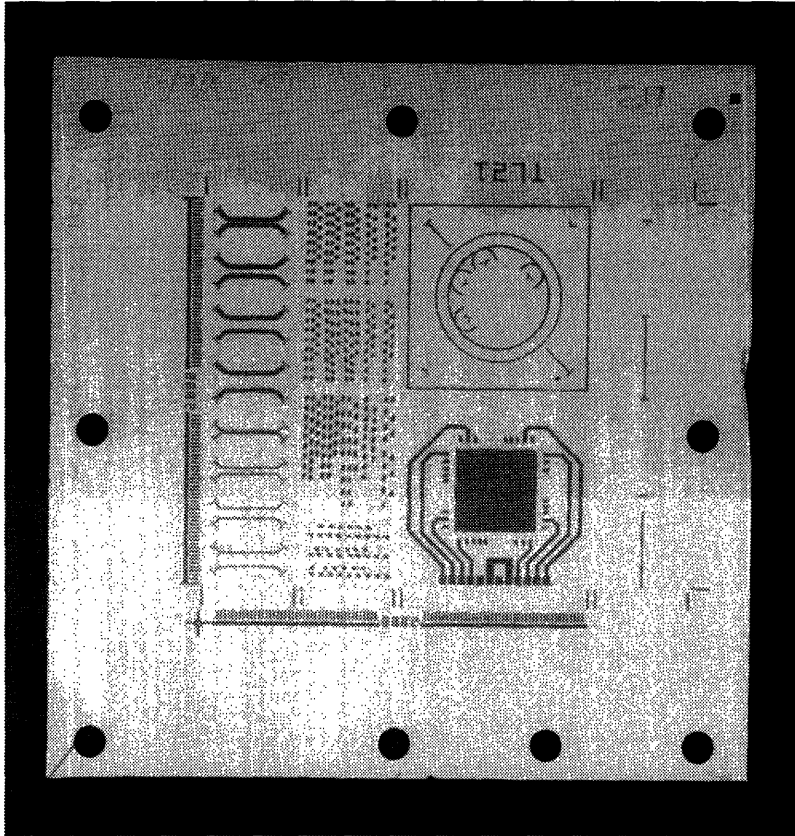


Figure 4.1: A typical LTCC circuit

These hybrid circuits offer an alternative to integrated circuits (IC) and printed circuit boards (PCB). Hybrids offer many advantages, including in the following aspects:

- interconnectivity, packaging and integration with IC's and host boards
- high-frequency or microwave circuitry requirements
- high thermal conductivity of substrate material (good heat dissipation)
- printable resistors, conductors, capacitors and inductors
- relatively low cost for low volume production

⁶ "Low-temperature" and "co-fired" refer to specific processing options, the discussion of which are beyond the scope of this thesis.

As have been successfully achieved for decades, thick-film circuits⁷ have been produced for consumer, industrial and military purposes. Advances in the field, such as laser-trimming for printed component adjustments, have made thick-film and LTCC circuits a viable option for certain applications. Improved machines and tighter controls on material, including ink and substrates, have also led to improved performance by LTCC circuits.

The technology of multiple layered circuits offers another advancement to the hybrid circuitry field. By stacking many layers of substrate, each with a conductor pattern, with conductors connecting circuits between layers, valuable space on the surface layers can be used for important resistors, capacitors, inductors, IC's, mounting pads and other devices. The added layers allow for overlapping conductor lines not easily achieved on a single layer of substrate, and thus *laminates* of numerous printed substrates can be a useful configuration.

Taken one step further, if printed components, including resistors, can be printed on internal layers of laminates, then the patterns of printed components can fully exploit the three dimensions of stacked circuits. This configuration also frees the surface layers for components that cannot be placed internally. However, the technology of producing accurate and precise *buried resistors* is not well-understood nor well-executed. Since correction operations such as laser-trimming cannot be performed on components on internal layers of a fired laminate, buried resistors must be printed to within high tolerances in order for the end product to meet specification. Due to process effects not fully identified, buried resistors still fall short of their desired potential.

4.1.2 Manufacturing System Overview

The manufacturing system under study currently produces LTCC circuits, with some configurations including buried resistors. However, as specifications are not met on many laminates from inaccurate buried resistors, the volume of production must be increased in order to produce enough acceptable circuits for an order. This production increase, however, is costly and loads the manufacturing line that could otherwise be making other products. As costs rise, the demand for these circuits shrinks, and customers look for alternatives to the LTCC circuit. In some cases, there is no viable alternative, so the pressure is levied on the manufacturer to find a solution.

⁷ Thick-film circuits is a category of circuits in which components are usually applied by screen printing, then fired and cooled. Thin-film refers to deposition of component films, followed by photoprocessing and etching.

The critical output parameter is the resistance of the resistors, which affects all segments of the overall circuit. Although circuit patterns are designed carefully off-line in an attempt to eliminate the need for post-process corrections (which internal layers do not physically allow), the resistance values are still not predictable nor satisfactorily close to the intended value. This is a case in which the predicted model for resistance is not accurate enough, and where the manufacturing system must be studied to find the sources of deviation from the target value of resistance.

Material

The main constituents of an LTCC resistor are the substrate and the ink. The substrate is a thin ceramic sheet of approximately 100 microns (~4 mils) thick in its flexible, unfired state. The ceramic sheet can be chosen in different thicknesses.

The inks tested vary in compositions and properties. A typical composition of an ink consists of ruthenium, titania, amorphous silica and a low melting temperature sealing glass such as lead zirconium manganese copper zinc boroaluminosilicate glass. Six resistive inks, often used for surface resistors with silver, silver palladium and gold conductors, have been considered for buried resistor systems. Among other properties, the rated resistivities and viscosities vary from ink to ink.

Basic Operations

The operations required to transform the materials into the finished product are complex despite the small number of materials. As will be detailed in Section 4.3.1, the manufacturing system for buried resistor systems includes the following process steps: cutting of ceramic tape, drilling of via holes in tape, via filling, conductor printing, resistor printing, cavity cutting, collating and stacking, lamination, green cut, burn-out and firing, and cover-coat and trimming to size.

This is similar to the current production process order for surface printed resistors, except that in surface resistor systems, resistor printing can occur after burn-out and firing. Although the process steps themselves are the same, the order in which they occur and the effects on the material and resulting properties can differ greatly. Firing a laminate *after* resistor printing, for example, means that the resistors undergo a process that did not apply when firing occurred *before* resistor printing. Also, the interactions, if any exist, between the ink under heating and the enclosing ceramic substrate may be an issue.

Pursuing buried resistor configurations significantly changes the transformation process. Product failures and other poor results indicate that new phenomenon are

occurring from the more traditional surface resistor configurations. Thus, this case-study provides the research with great potential for application.

4.1.3 Company Constraints

The company encounters similar non-technical issues that occur at other industrial workplaces. The constraints in this organization include the following:

- Current production of non-buried resistor configurations limits the amount of experimentation that can be conducted without endangering delivery schedules of current contracts. Buried-resistor experiments would divert resources away from normal production demands. These resources include manpower, money, materials, time and equipment.
- Manufacturing supervisors, whose more direct responsibilities lay with the successful manufacture of product in demand, are “interested” in optimizing and understanding more about the system processes, but cannot justify significant trade-offs that may endanger short-term successes.
- Factory personnel are very concerned about their job security, and any attempts to investigate operations and to conduct fact-finding activities may seem to pose risks to their economic and professional stabilities. Training for additional, “outside” tasks that distract from daily responsibilities can be seen as detrimental to their primary job function and subsequent review.
- Company managers and overseers, with budgetary and time concerns, want justification for experimentation and any other diversions from current production efforts.
- Geographic separation between research facilities and production lines is nonnegligible, so scheduling and employee availability become issues and constraints.
- Technical expertise is similarly divided, and although personnel are well-qualified in their fields, concurrent engineering efforts and round-table discussions for problem-solving often encounter logistical constraints as well as insufficient interdepartmental scientific understanding. That is, communication between workers having different scientific and engineering backgrounds can be unfruitful if there is little overlap in technical comprehension.

The collection of these constraints poses a challenging scenario for those wanting to evaluate and optimize the manufacturing system. Not only are the manufacturing operations not fully understood, but there are social and managerial constraints that can limit efforts to improve production.

4.1.4 Description of Dataset Information

As an initial attempt to gather information about buried resistor LTCC configurations, the research laboratory conducted a basic experiment of varying resistor geometries and locations. While certain key features were represented in the design variables, it was admitted that few critical parameters were known at the time the experiment.

Six resistive inks of interest to the company were included in the tests. For each ink, four laminates were manufactured, each consisting of twenty-one layers of ceramic substrate. Figure 4.2 shows depicts a laminate in the designed experiment, with a cutaway view exposing inner layers.

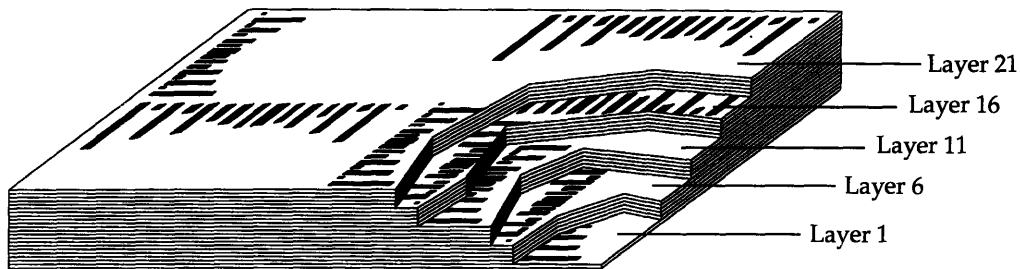


Figure 4.2: A cutaway view of the laminate structure. Buried resistors are printed on layers 1, 6, 11 and 16. Thickness is exaggerated to show individual layers.

Layer 21 is an external layer, with its resistors exposed on the surface, while the other layers' resistors are internal to the laminate structure. Layers 1, 6, 11, 16 and 21 are printed with varying resistor patterns, while the other layers feature only conductor lines and vias that conduct between layers.

The resistor patterns vary from layer to layer. For example, the resistor patterns of layers 11 and 16 are shown in Figure 4.3.

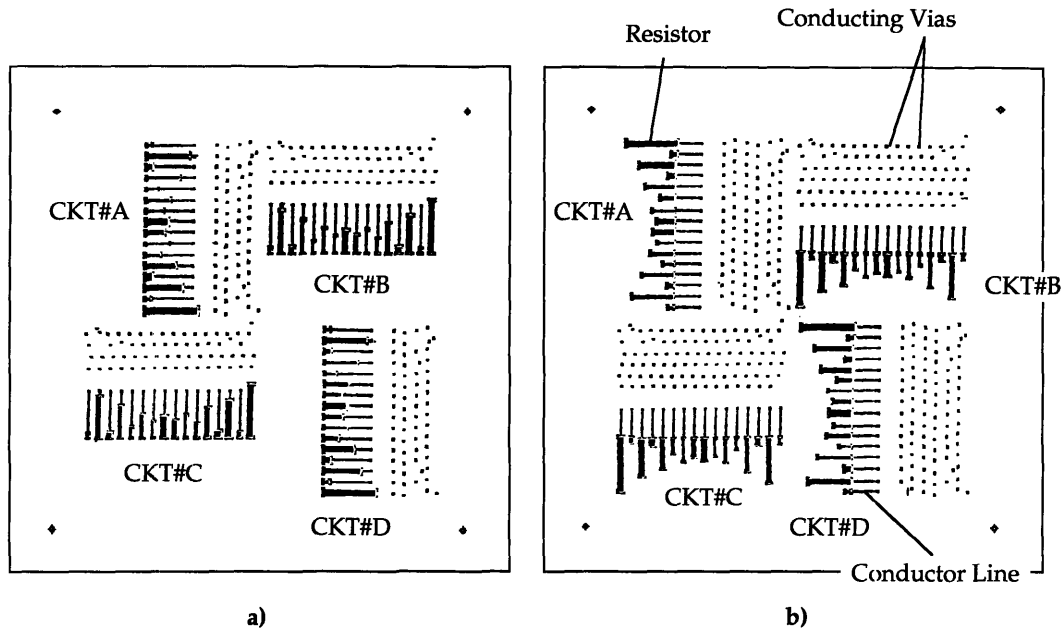


Figure 4.3a: Resistor pattern on layer 11; b: Pattern on layer 16. Notice the slight differences in location of resistor rows from layer to layer. The real size of each sheet is approximately five inches square.

The quadrants, or *circuits* (CKT#), are designated as A, B, C and D, and their orientations can be discerned from Figure 4.3. Thus, circuits A and D are oriented in the same direction, while circuits B and C are at an orthogonal angle. Each row in each quadrant of resistors consists of 16 resistors, having combinations of widths of 20, 30, 40 and 50 mils and aspect ratios of 0.5, 3.0, 5.5 and 8.0. Thus, the designed length of the smallest resistor is 10 mils (20 mils wide, aspect ratio of 0.5), and the largest resistor is designed as 400 mils long (50 mils wide, aspect ratio of 8.0).

Notice that the general location of the rows or columns of the resistors are moved to different areas of the layer quadrants. However, the resistor geometries are in the same order in a given row, although each row may be rotated 180 degrees on another layer, maintaining the same orientation. For example, the row of resistors in CKT#B on layer 11 is located higher in the quadrant than is CKT#B on layer 16, while the two rows are oriented 180 degrees from each another. Thus, the CKT#B resistors all “point” in the same direction.

In total, for each of six inks, there are 64 resistors on each of 5 resistor layers on each of 4 laminates. This results in 1280 resistors for each ink, or 7680 total resistors in the experiment. For each resistor, a resistance measurement in ohms was recorded. The input variables for this experiment are the design variables of ink, resistor width, aspect ratio, location on layer, orientation, layer in laminate, and laminate (or sample).

4.1.5 Notation and Conventions

For this case study, this paper will employ the following notations and abbreviations:

- The six resistive inks are referred to as ink I, II, III, IV, V, and VI.
- A circuit, or quadrant, is designated as *CKT#*, for circuits A, B, C and D.
- Layer is represented as the variable *Z*, with values of 1, 6, 11, 16 and 21.
- Position on a layer is assigned an (x,y) coordinate, corresponding to the approximate center of the resistor, from an origin at the center of the layer, using a Cartesian coordinate system.
- Resistance is abbreviated as *R*; width as *W*; length as *L*; thickness as *t*; aspect ratio as *AR*, equal to length divided by width.
- Resistors are classified as *N% resistors*. Common industry standards for component resistors include 5% and 10% resistors at 3σ capability (99.7% of manufactured resistors are within specification). In this document, a 1σ standard is used. Thus, a 15% resistor in this thesis means that 68.3% of the resistors are within $\pm 15\%$ of the target resistance.

4.2 Non-Parametric Statistical Modeling

Previous efforts to analyze the resistor data used commonly applied numerical methods to quantify the resistor behavior. In the characterization reports of the company, curve-fitting approaches and distribution plots were consulted in efforts to understand the resistance measurements and possible underlying causes. These efforts encountered limited successes, but at least provided a starting point from which further studies could be originated or comparisons drawn.

4.2.1 Quality of Fit

Past efforts to model the resistance behavior utilize curve-fitting approaches first, then attempt to associate the equation with possible physical or engineering explanations.

One such effort uses Weibull statistics distribution plots to analyze the data. The resulting relationship is of the form:

$$\ln R = m \cdot AR \quad (4.1)$$

where *m* is the slope of Weibull distributions over $\ln R$. It is noted that the statistics distribution showed a distinctive separation of values compared to aspect ratios. The

analysis is divided among the six inks and also over each resistor layer, with a separate m for each aspect ratio on each layer. What results is a look-up table of predicted resistances using localized analyses.⁸ However, comparison of the table's values with the actual resistances shows that (4.1) is a poor model.

Another modeling effort beginning with statistical and numerical fits pursues a form based upon the parameters of length, width and layer for each ink as:

$$R = K \frac{L^\alpha}{W^\beta Z^\gamma} \quad (4.2)$$

These fits result in correlation coefficients often greater than 0.99. However, as noted in [Kiemele, 1990], these coefficients are only general indicators of closeness of fit. Evaluation of the models give values predicting 6%, 15% and 46% resistors for inks IV, V and VI respectively, with each ink having its own values for K , α , β and γ [Ho, 1994].

Pursuing a model equation for each layer based upon Equation (4.2), another form is used [Ho, 1995a]:

$$R = K \frac{L^\alpha}{W^\beta} \quad (4.3)$$

For inks IV, V and VI, this subdivision into individual layers results in slightly improve resistor predictions. For example, for ink VI, the data suggests that over all layers, 46% resistors are attainable, while with localized analyses at each layer, as low as 37% resistors are predicted. Using (4.3), each K , α and β are specific to the given ink and layer, similar to the method producing (4.1). This supposed improvement is a direct result in choosing smaller subsets of the dataset that include more homogeneous data.

Also, (4.3) is modified with additional terms to reflect trends discernible in dataplots, resulting in:

$$R = K \frac{L^\alpha}{W^\beta} e^{\lambda L} e^{\omega W} \left(1 + \varepsilon_1 L^2 + \varepsilon_2 \frac{1}{L^2} + \dots + \varepsilon_5 \frac{1}{L^5} \right) \quad (4.4)$$

For example, with ink VI, the localized per-layer statistical fits improve the predictability from 37% to 16%–21%. Other inks demonstrate similar improvements from these model forms.

4.2.2 Limitations

As is typical of curve-fitting and numerical methods, the correlation coefficients of these models can be quite high, and N% values can appear quite low. However, as briefed in

⁸ The source of this data is a company-proprietary report "LTCC Resistor Modeling," April 1994.

Section 3.5, these localized models may not satisfy interpolation and extrapolation applications.

The results using (4.1) through (4.4) can be tabulated into a look-up table, which gives constants specific for each ink and layer based upon statistical best-fit analysis. Given that the data is representative of future resistor behavior, these tables may be used for designing buried resistor configuration laminates *if* the resistors are placed on the *same* layers included in the experiments and manufactured using the same materials and processes. However, what if resistors are desired on other layers, ones not included in the dataset? For example, what if a resistor is placed on layer 3 or layer 17?

Interpolation between localized models is questionable. While the model equations may fit the data for Z values for which there are experimental resistors on the represented layers, there is little assurance that the models are equally applicable for the intermediate layers should resistors be printed on those. Linear interpolation or a second-order continuous equation may turn out to approximate resistor behavior, but because the models were not based on any physical or scientific effect, there is no guarantee that intermediate resistor layers, for example, may function in any accordance with localized numerical models for specific individual layers.

Extrapolation is even less applicable. While functions of variables bounded by analyzed datapoints can be approximated by interpolation, values beyond the limits of tested data are more difficult to predict with numerical methods not modeling actual process effects. In this case, extrapolation issues limit the predictability of geometries beyond the widths, lengths, aspect ratios and layers used in the experiments.

These equations do not usually provide any insight into the mechanisms which are causing variation in the data from the predictive base equation. Often, as with polynomial equations and forms similar to (4.4), for example, is it difficult to extract any understanding of operations and the processes from equations with a series of terms of many variables with combinations of exponents.

The apparent trade-off in these modeling efforts is that the more general the equation encompassing a large range of design parameters, the poorer the fit and thus the larger the N% value. However, the smaller the subset of data used to form each element in a look-up table, the less applicable to a range of design variables, despite the improvements in standard deviation or N% values.

4.3 Methodology Implementation

Here the methodology explained in Chapter 3 is applied to the manufacturing system and the data of the buried resistor experiment. Qualitative modeling of the system and the operations is demonstrated, then the iterative process of quantifying possible effects to the product follows.

4.3.1 System Operation Flowchart

As explained in Sections 3.1 and 3.2, developing the operation flowchart is an essential step in the methodology. The representation of the manufacturing system is illustrated in this subsection.

Basic Operation Flowchart

For the LTCC system, the major steps in the manufacture of buried resistor configuration laminates are as follows:

- Cut the ceramic tape from the roll into required squares
- Drill or punch via holes in the tape according to the circuit design
- Fill the vias with conductive material
- Print conductor lines on the tape according to the circuit design
- Print resistors on the desired layers
- Cut cavities in the layers to allow for packaging features and external device attachment
- Collate and stack the multiple layers for a laminate
- Laminate the layers together
- Cut the unbaked laminate into the approximate final dimensions
- Burn-out and fire the laminate
- Trim the laminate to the final size

These steps can be represented by an operation flowchart, shown in Figure 4.4.

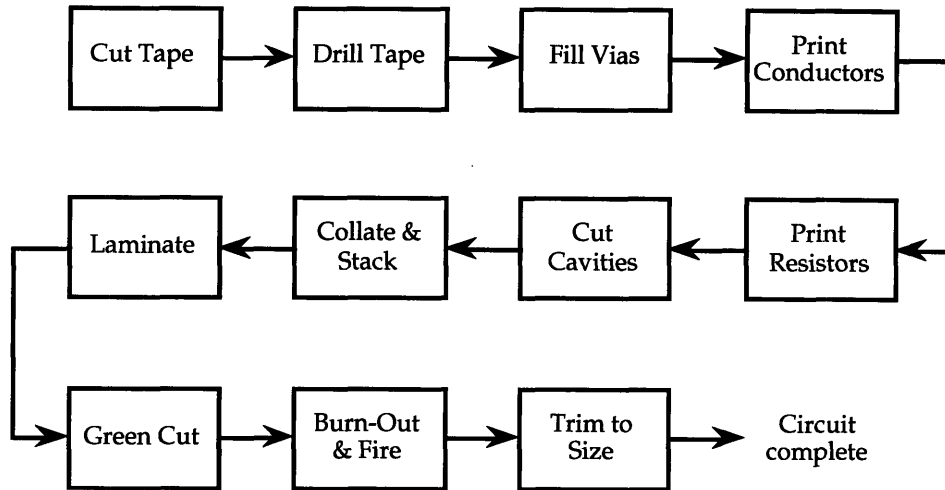


Figure 4.4: The major operations in the LTCC manufacturing process for buried resistor configurations.

Subdivision of Operations

Recalling that each operation listed above is a combination of material throughput, machine and operator interaction and other contributors to the process, it is necessary to further subdivide each operation into its component suboperations. For example, the step of printing resistors involves the substrate with conductor lines already printed, the introduction of a printing machine with a new pattern and screen, and a different ink. Also, printing involves set up of the screen, ink and substrate, machine setting adjustment, the actual deposition of ink through the mesh, and drying. A more detailed representation of the resistor printing operation is shown in Figure 4.5. Note the convergence of two parallel streams, the screen preparation and the ink preparation, into the main process flow.

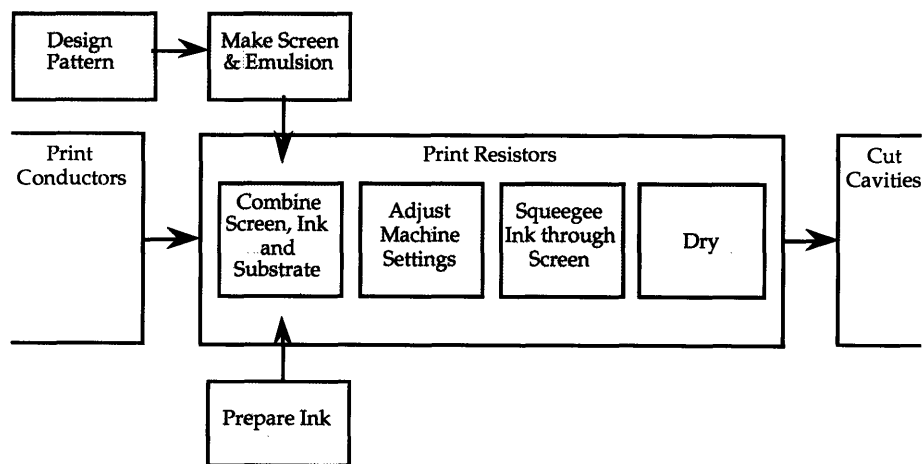


Figure 4.5: The resistor printing operation with more detailed substeps.

The steps of the resistor printing operation may also be refined into more detailed divisions as well. For example, the cell “Adjust Machine Settings” may be expanded into the individual settings that can be adjusted, including any outside influences such as operator biases or instructions. Similarly, the “Dry” step can be further expressed as the removal of the substrate from the machine, placement on a drying rack, and the environmental control steps.

It may be helpful to develop and refer to a cause-and-effect diagram at this stage. For example, Figure 4.6 is a simple fishbone diagram suggesting potential error sources for the resistor printing operation. As typical of this diagramming tool, the six categories of environment, measurement, method, operator, materials and machine assist in organizing thoughts to refine a large operation.

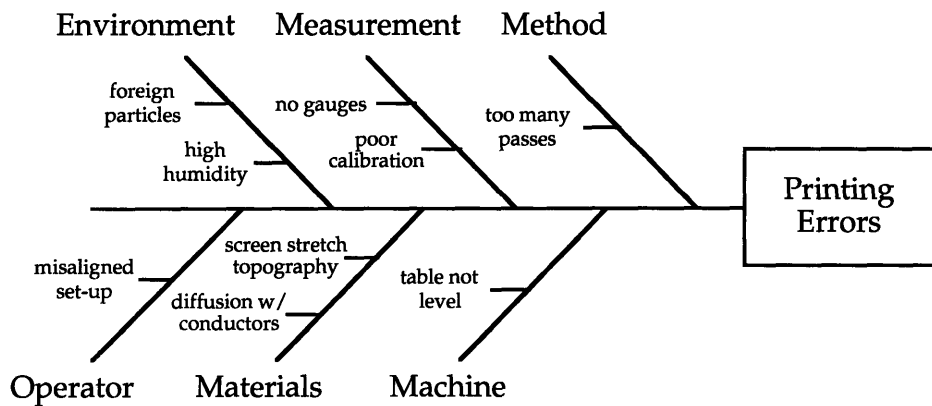


Figure 4.6: A cause-and-effect diagram of potential error sources in the printing process.

As Figure 4.6 implies, the printing operation can be virtually divided. Environmental factors such as ink impurities and contamination can occur simultaneously with the actual physical printing action, so the detailed representation of the printing operation in Figure 4.5 can include virtual divisions.

4.3.2 Quantitative Modeling

Here we illustrate the steps to model system operation using particular LTCC operations, from variable set selection to mechanism contribution formulation. The goal of the application of the methodology is to find sources of error to or secondary effects of the resistance of the printed resistors and to develop a predictive equation that more closely models the resistor performance.

Variable Set Selection

In the LTCC system, high level variables are used to develop the base equation, developed later in this section. These design variables include the dimensions of the resistor (L, W, t) and the location of the resistor in the laminate (x, y, Z). Note that these variables can be expressed as independent variables used during the product design, but also as dependent variables of the lower level manufacturing process mechanisms. That is, the actual dimensions of a printed resistor is a function of the printing process parameters such as material properties and machine settings. We use these product variables in this manufacturing system's variable set. Also note that the resistor geometry and location can be measured and recorded for each laminate.

The analysis treats each ink as a separate case, which may imply that this analysis is also employing a localized modeling technique. However, ink type is a *categorical variable*, as opposed to layer Z , a *continuous variable*, which can be *extensively measured* [Otto, 1995]. That is, the parameter Z is considered continuous because it directly relates to a dimension (depth or height of laminate), which is itself a continuous variable. Ink type, however, has not yet been adequately parameterized and cannot be included in the variable set. Each ink is a discrete material choice, and the parameters that fully describe and relate one ink to another have not been determined. If the inks can be characterized by a sufficiently comprehensive set of variables, then the analysis may pursue a model including ink type in its variable set (i.e. find one model that is applicable to all six inks).

First-Order Base Equation

For the resistors of the LTCC system, a base model of resistance is needed. From basic physics theory, a block of resistive material has a resistance equal to:

$$R = \rho \frac{L}{Wt} = \rho_s \frac{L}{W} \quad (4.5)$$

where ρ is the bulk resistivity of the material, and ρ_s is the sheet resistivity. Equation (4.5) serves as the first-order base equation and has been well-correlated ($r^2 > 0.90$) with the data as an acceptable basic model R_{base} .

Comparison of Equation (4.5) to (4.2) through (4.4) should illustrate that the numerical modeling methods result in models similar to the theory-based equation.

Mechanism Identification

Using fishbone diagrams such as the one presented in Figure 4.6, possible secondary effects are identified. Based on discussion in literature on screen printing such as [Jones, 1982] and [Riemer, 1988a], a mechanism involving screen stretch and ink flow is developed. This mechanism is referred to as *resistor surface topography*.

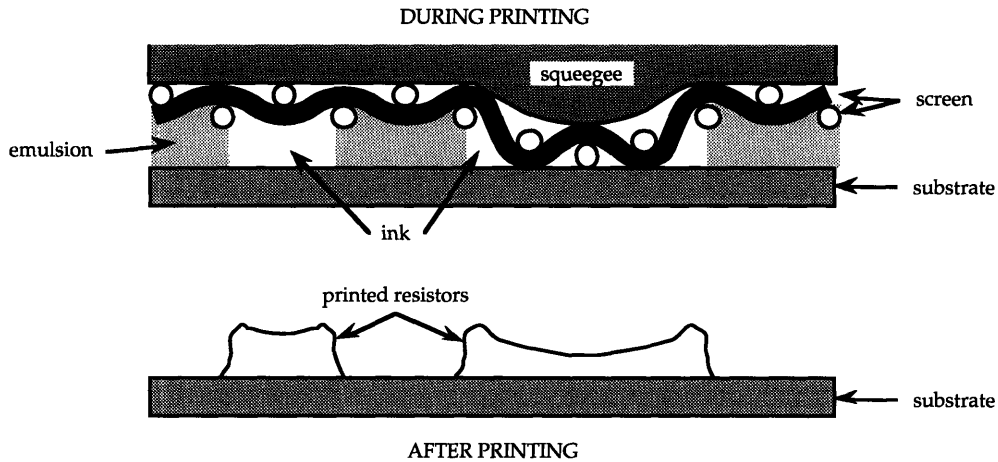


Figure 4.7: Resistor topography – the effect of the resistor pattern and screen stretch on resistor thickness. Notice that for resistors of small width or length, the thickness is more uniform than for a resistor of larger dimensions.

During screen printing, the downward force of the squeegee on the screen can cause nonuniform film thickness. For resistors of large enough dimensions (i.e. width and length) the squeegee can deflect the mesh in the middle of the resistor pattern regions, resulting in a thinner film than at the sides of the resistor region, where the emulsion layer prevents significant deflection. For resistors of smaller dimension (e.g. thin and short resistors) the deflection effect is less significant, and thus the surface topography is more flat. This phenomenon is illustrated in Figure 4.7.

Another mechanism involves the interaction between the resistor and the conductor, a mechanism involving an added *contact resistance*. When two materials of dissimilar properties meet, such as printing inks, there can be a region of higher resistivity resulting from less conducting content or interface voids from incomplete ink adherence or surface roughness. Figure 4.8 illustrates the location of the contact resistance effect.

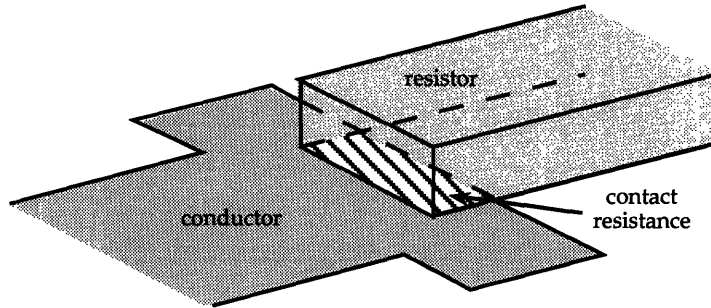


Figure 4.8: Contact resistance – when two dissimilar materials meet, added resistance may result from a decreased conduction content (e.g. from chemical reactions) or interface voids.

Other mechanisms have been identified and evaluated, but due to variable confoundedness cannot be resolved. These mechanisms are discussed in Section 4.3.5.

Form of Mechanism Contribution

Returning to the topography mechanism, a physics model of the effect is derived. Since the geometric traits of the resistor postulated in this mechanism is rather complex, a characterizable geometry is selected, with an easily derived resistance. Figure 4.9 illustrates the simplifications made to allow for appropriate approximations of the topographical effects.

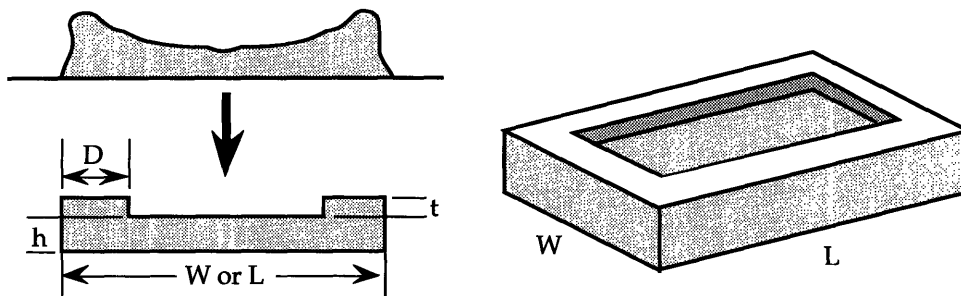


Figure 4.9: Resistor topography – geometric simplifications made to approximate the form of the mechanism contribution.

Defining a multiplying modifier to Equation (4.5) as $F_{topography}$, the approximate contribution of a topography effect can be derived. Recall the base equation of (4.5):

$$R_{base} = \rho \frac{L}{Wt_{stat}} \quad (4.5)$$

Also, a resistor of the geometry shown in Figure 4.9 has a resistance of:

$$R_{topography} = \frac{2\rho D}{W(t+h)} + \frac{\rho(L-2D)}{2Dh+Wt} \quad (4.6)$$

Thus, the modifier $F_{topography}$ can be derived as:

$$F_{topography} = \frac{R_{topography}}{R_{base}} = \frac{\frac{2\rho D}{W(t+h)} + \frac{\rho(L-2D)}{2Dh+Wt}}{\rho \frac{L}{Wt_{stat}}} \quad (4.7a)$$

which can be expressed as:

$$F_{topography} = \frac{2Dt_{stat}}{L(t+h)} + \frac{Wt_{stat}}{2Dh+Wt} - \frac{2DWt_{stat}}{L(2Dh+Wt)} \quad (4.7b)$$

where D , t and h are parameters describing topography features, and t_{stat} is a representative thickness of the resistors.

Notice that (4.7b) contains variables not included in the designed experiments: D , h and t . Also, (4.7b) includes a non-linear function of W which cannot be linearly regression fit. An approximate function is $\ln W$. Thus, the contribution can be approximated and reduced to:

$$F_{topography} = K_1 \frac{1}{L} + K_2 \ln W + K_3 \frac{\ln W}{L} \quad (4.8)$$

This form of the contribution can be tested and statistically evaluated without any additional experiments. The mechanism carries with it some requirements on the magnitude and sign of the coefficients K_1 , K_2 and K_3 . As length increases, the thickness of the resistor should decrease asymptotically, and therefore the factor $F_{topography}$ should exhibit a trend with $\left(-\frac{1}{L}\right)$.

This mechanism would occur during the printing operation as part of the actual pressing of the ink onto the substrate. Thus, we update the operation flowchart cell to accommodate this mechanism, as shown in Figure 4.10. If it is not supported by data, the corresponding model contribution cell may be filled with a 1 (one) or \emptyset (null) to indicate no effect, or the mechanism cell may be removed altogether from the flowchart.

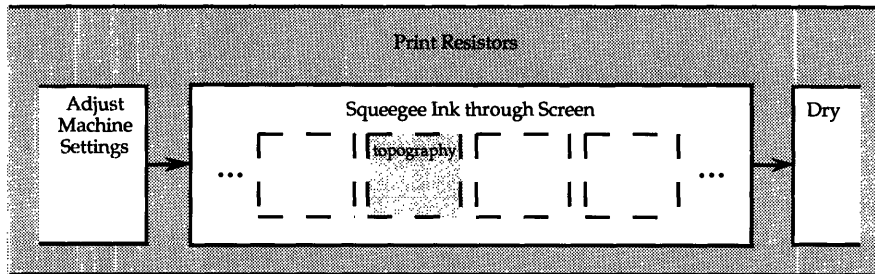


Figure 4.10: Representing the topography mechanism on the operation flowchart. The mechanism supposes the resistor would have an uneven surface as a result of the squeegee pressing down on the mesh. This occurs during the actual physical printing step.

Notice that the topography mechanism is given a virtual representation (box outline is dashed) as discussed in Section 3.2.2. This indicates that during the actual printing process, there may be other secondary effects that occur simultaneously.

For the contact resistance mechanism, a resistor has a resistance of:

$$R_{contact} = \rho_s \frac{L}{W} + \frac{2K}{Wl} \quad (4.9)$$

where K and l reflect upon interface characteristics between the conductor pads and resistors. Thus, the modifier $F_{contact}$ for this mechanism is:

$$F_{contact} = \frac{R_{contact}}{R_{base}} = K_1 + \frac{2K}{\rho_s l} \frac{1}{L} \quad (4.10)$$

where K_1 is a scaling term. For comparison with the data, (4.9) is converted into:

$$F_{contact} = K_1 + K_2 \frac{1}{L} \quad (4.11)$$

In this form, with certain size and sign conditions on the coefficients, the mechanism can be tested with the experimental data. For this mechanism, the effect of the additional contact resistance should become asymptotically less significant as the resistor length increases.

In both (4.8) and (4.11) the terms are functions of L and W , which were both varied in the designed experiment. Thus, the model contribution forms can be tested using the regression analysis tools and the data measured at the company.

4.3.3 Comparison with Data

Before correlating the forms of the mechanism contributions to the data, the data itself requires some attention. For example, some of the resistors tested were “open” or “shorts” so these resistors were removed from the dataset. Outliers were conservatively identified; only those points outside a few standard deviations of its associated data cluster which were not part of a discernible trend were removed from the data sample.

As mentioned in Section 3.3.4, some issues must be resolved before applying statistical tests to the data. Recalling the four questions:

1. *Does the mechanism affect all or only a selection of products for a range of material and process inputs?*

The topography effect should apply to all inks, but may not be supported to the same degree by each ink. Variables such as particle size and viscosity may cause some inks to settle out more flatly than others. Also, due to the limits in screen mesh definition, the

mechanism contribution forms should be tested on data not including the smaller resistors (e.g. $AR \leq 0.5$) as topography effect may be clouded by the limiting effects of the screen size and accompanying mechanism effects.

The contact resistance mechanism should be tested for all ink, but again, low aspect ratios are not included due to the other problems of printing fine dimensions. This mechanism may not appear in all six inks as their interactions the conductor inks may differ.

2. *How would the effect be described by an equation using the chosen variable set?*

As given before, the equations for the example mechanisms include terms of L and W as:

$$\text{topography: } F_{\text{topography}} = K_1 \frac{1}{L} + K_2 \ln W + K_3 \frac{\ln W}{L} \quad (4.8)$$

$$\text{contact resistance: } F_{\text{contact}} = K_1 + K_2 \frac{1}{L} \quad (4.11)$$

3. *What is the specific behavior of the effect on the product?*

Topography effects should have a $\left(-\frac{1}{L}\right)$ behavior, contact resistance a $\left(+\frac{1}{L}\right)$ trend.

4. *How do the material and process parameters enter into the description of the secondary effect?*

This issue has been resolved by the derivation of (4.8) and (4.11), the unknown material and process parameters being accommodated by and modeled into the coefficients K_i . If known, characteristic values of material and process parameters can be used to estimate the expected magnitude of the coefficients.

Recalling the general resistance equation from (4.5), consider the measured resistances R_{measured} :

$$R_{\text{measured}} = \left(\rho_s \frac{L}{W} \right)_{\text{measured}} \quad (4.12a)$$

As length L and width W are not measured and thus considered constant in this analysis, (4.12a) can then be formalized as:

$$R_{\text{measured}} = \rho_{s,\text{measured}} \frac{L}{W} \quad (4.12b)$$

Similarly, for the base equation R_{base} :

$$R_{\text{base}} = \left(\rho_s \frac{L}{W} \right)_{\text{base}} = \rho_{s,\text{base}} \frac{L}{W} \quad (4.13)$$

The regression analyses using (4.8) and (4.11) are performed with data in the modulated form of:

$$\frac{R_{measured}}{R_{base}} = \frac{\rho_{s,measured} \frac{L}{W}}{\rho_{s,base} \frac{L}{W}} = \frac{\rho_{s,measured}}{\rho_{s,base}} \quad (4.14)$$

where $\rho_{s,measured}$ is the equivalent sheet resistivity from measured data as in (4.12b), and $\rho_{s,base}$ is determined by statistical analysis. In the following tables, the modulated data of (4.14) is shown as K_{meas}/K_{stat} , the dependent variable in the regression analyses.

Topography Correlation

To check for the required $(-1/L)$ behavior, an initial regression table is generated. For example, analysis of ink IV gives Table T4.1, which confirms the basic trend. The standard deviation in Table T4.1, shown as $s=0.0952$, or a 9.5% resistor, is smaller compared to the standard deviation using the base model ($s=0.1203$), so the regression fit is a statistical improvement. Although the overall correlation coefficient is a low 37%, the t-ratios and probability values indicate that the regression terms are not randomly related to the data and that there is indeed a correlation between the regression term and the dependent variable. The low 37% correlation suggests that there are many unresolved secondary effects remaining.

Dependent variable is: Kmeas/Kstat				
cases selected according to ink IV				
7680 total cases of which 6982 are missing				
R squared = 37.5%		R squared (adjusted) = 37.4%		
s = 0.0952 with 698 - 2 = 696 degrees of freedom				
Source	Sum of Squares	df	Mean Square	F-ratio
Regression	3.78234	1	3.78234	417
Residual	6.31255	696	0.009070	
Variable	Coefficient	s.e. of Coeff	t-ratio	prob
Constant	1.13157	0.0074	153	≤0.0001
1/L	-19.2442	0.9424	-20.4	≤0.0001

Table T4.1: Regression table confirming required trend for topography effects. Note that the coefficient for $1/L$ is negative, as derived.

Now that the trend has been confirmed, the regression fit with the more appropriate terms from (4.8) are tested. In Table T4.2 are the results for ink IV, showing t-ratios and probabilities supportive of the regression terms.

Dependent variable is: Kmeas/Kstat				
cases selected according to ink IV				
7680 total cases of which 6982 are missing				
R squared = 51.9% R squared (adjusted) = 51.7%				
s = 0.0837 with 698 - 4 = 694 degrees of freedom				
Source	Sum of Squares	df	Mean Square	F-ratio
Regression	5.23654	3	1.74551	249
Residual	4.85835	694	0.007001	
Variable	Coefficient	s.e. of Coeff	t-ratio	prob
Constant	0.099003	0.0742	1.33	0.1823
1/L*lnW	-24.7906	2.829	-8.76	≤0.0001
1/L	68.7153	9.248	7.43	≤0.0001
lnW	0.286912	0.0209	13.7	≤0.0001

Table T4.2: Regression table of the specified terms of the topography mechanism contribution equation. Notice that the fit, or correlation, increases over Table T4.1.

Notice that the correlation coefficient has increased to 51% in Table T4.2 versus 37% in Table T4.1. Again, as explained in Section 3.3.5, this coefficient is of limited use in indicating performance limits, it does show a relative improvement in modeling analysis. Also note the standard deviation has decreased to $s=0.0837$, or an 8% resistor, an improvement over the trial regression of Table T4.1 and the base model variation.

The regression analyses for other inks, however, give results not conforming to the required behavior trend for topography effects, the negative proportionality to $1/L$. Thus, these inks do not demonstrate the topography mechanism.

Contact Resistance Correlation

Repeating the regression exercise for the contact resistance mechanism gives tables similar to Table T4.3, conducted for ink VI.

Dependent variable is: Kmeas/Kstat				
cases selected according to ink VI				
7680 total cases of which 6915 are missing				
R squared = 60.4% R squared (adjusted) = 60.3%				
s = 0.3068 with 765 - 2 = 763 degrees of freedom				
Source	Sum of Squares	df	Mean Square	F-ratio
Regression	109.463	1	109.463	1163
Residual	71.8045	763	0.094108	
Variable	Coefficient	s.e. of Coeff	t-ratio	prob
Constant	0.325897	0.0227	14.4	≤0.0001
1/L	98.7856	2.896	34.1	≤0.0001

Table T4.3: Regression table for the contact resistance mechanism for ink VI. Note the coefficient for the $1/L$ term is positive as required.

Because the mechanism formulation is simple and only considers one linear regression term, the function $1/L$, no trial analysis is performed as was needed for the topography mechanism.

4.3.4 Quality of Fit

A summary of the analysis for the topography mechanism and the contact resistance mechanisms are presented in Table T4.4. For some inks, the predictability of the resistance improved upon modification of the base equation with the secondary effect contribution. That is, lower sigma values were obtained from comparing the data with the modified model equation:

$$R_{modified} = R_{base} \cdot F_{mechanism} = \rho_s \frac{L}{W} \cdot F_{mechanism} \quad (4.15)$$

ink	N% rating (1σ) from target of base model	N% (1σ) with topography mechanism	N% (1σ) with contact resistance mechanism
I	17.98%	not supported	17.91%
II	67.30%	not supported	67.20%
III	20.91%	not supported	20.21%
IV	12.03%	8.35%	not supported
V	15.48%	not supported	13.51%
VI	48.71%	not supported	31.72%

Table T4.4: Summary table for the two mechanisms. Only ink IV supported the topography mechanism, while only ink IV did not support the contact resistance mechanism. Note the improved fit of the model equation from the base model to the modified equation. For example, a 49% resistor of ink VI is improved to a 32% resistor.

Since the mechanisms both involve the same $1/L$ term, it is not surprising that no ink supported both mechanisms. This may imply that one secondary effect is dominating another or that the two effects are statistically canceling out.

Comparison to the numerical results in Section 4.2.1, the improvements here may seem less significant than the fits obtained case-by-case, layer-by-layer Equations (4.3) and (4.4). However, the modified base equation is not layer-dependent, and because (4.15) is based upon an engineering or physics explanation, interpolation and extrapolation among the geometry variables will provide more accurate results.

4.3.5 Other Mechanisms

Other mechanisms have been postulated as possible sources of secondary effects in resistor performance as shown in Figure 4.6. However, due to variable confoundedness, some of these mechanisms cannot be fully supported nor refuted.

For example, in the designed experiment, the location and orientation of the resistors have been confounded. That is, knowing the (x,y) location of a resistor automatically gives the layer Z and the orientation of the resistor on the substrate. Also, the arrangement of the different sizes of resistors are not varied. In each row (the resistors in a quadrant on a layer) there is the same order of resistors of different lengths and widths. For example, the longest and widest resistor (400 mils long x 50 mils wide) is always at the end of a row and next to the second-shortest resistor (15 mils long x 30 mils wide). Thus, there exists a confounded state among the variables x , y , Z and orientation, complicated by the lack of variation in arranging resistor geometries. Figures 4.2 and 4.3 show the interdependence of the resistors' (x,y) location and Z parameter.

Nonetheless, mechanisms can be developed to be evaluated at a later time when new information can be acquired without the variable confoundedness. Some possible sources of secondary effects are discussed below.

Non-Level Printing Table or Uneven Squeegee Pressure

Suppose the relative angle between the substrate on the printer mount and the squeegee stroke is nonzero, depicted in Figure 4.11. This will result in higher pressure on one side or one corner of the screen as the squeegee will deform under the added force, the relative distance between the squeegee and screen decreasing. [Riemer, 1988a] shows that increasing squeegee force decreases the deposition weight of the ink, which suggests the thickness of the thick film is thinner at locations of higher forces.

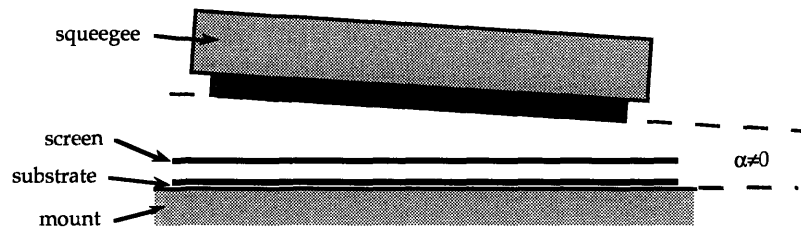


Figure 4.11: Nonzero relative angle between squeegee and the substrate surface. Uneven printing pressure may result in nonuniform film thicknesses along the print width throughout the stroke.

Thus, a trend can be postulated with this mechanism: thickness is, to first order, inversely proportional to the pressure, which is related to the (x,y) locations on the screen and substrate. As resistance is inversely proportional to print thickness by (4.5), one could expect a modulated or normalized resistance given by (4.14) to show a correlation with location. If the squeegee and screen are uneven with respect to either the x -axis or the y -axis, then this mechanism effect could be found by testing for a slope in x or y data. However, if the unevenness is not aligned with the axes, then slopes in both variables should result.

Therefore, a first-order approximation of a variation in thickness is:

$$\delta t \approx ax + by \quad (4.16)$$

where a and b linearly relate the position on the substrate to the difference in print thickness. The resistance $R_{\alpha \neq 0}$ can then be written as:

$$R_{\alpha \neq 0} = \rho \frac{L}{W(t + \delta t)} = \rho \frac{L}{W(t + ax + by)} \quad (4.17a)$$

Expanding in terms of thickness to uncover a first-order trend:

$$R_{\alpha \neq 0} \approx \rho \frac{L}{Wt} \left(1 - \frac{a}{t}x - \frac{b}{t}y \right) \quad (4.17b)$$

Now the mechanism contribution $F_{\alpha \neq 0}$ is derived:

$$F_{\alpha \neq 0} = \frac{R_{\alpha \neq 0}}{R_{base}} \approx \frac{\rho \frac{L}{Wt} \left(1 - \frac{a}{t}x - \frac{b}{t}y \right)}{\rho \frac{L}{Wt}} = 1 - \frac{a}{t}x - \frac{b}{t}y \quad (4.18)$$

For comparison with data, (4.19) is rewritten in terms of x and y only:

$$F_{\alpha \neq 0} = K_1 + K_2x + K_3y \quad (4.19)$$

where K_1 is near 1, and K_2 and K_3 indicate magnitude and direction of the incline.

This mechanism and the approximation (4.16) are complicated by possible nonlinear response of the squeegee, a rubber or rubber-like material. Thus, the relationship between squeegee pressure, ink flow and deposition or thickness is not likely easy to detail. However, a linear approximation may be adequate to discern whether this mechanism is occurring.

As noted before, however, confoundedness with Z does not allow positive results to totally confirm an (x,y) trend. In fact, the analysis does give statistical support to a location correlation reflected by (4.19), but it is possible that the differences in resistance is due to a secondary effect dependent upon a Z location

mechanism (recall that Z is confounded with x and y). Thus, it is not sound to confirm this trend until this confoundedness has been resolved.

Thermal Differences from Resistor Depth into Laminate

As the substrate is ceramic with a nonnegligible thermal diffusivity, heating differences can become a factor in LTCC circuits. [Prudenziati, 1994] indicates the fictive temperature of glass materials in inks is significant in the firing of samples. This suggests that the heating and cooling rates of ink constituents, as affected by the thermal response of the ceramic layers to the furnace environment, can be a significant factor in the resistance of the fired ink.

The furnace heats the laminates from the bottom. This suggests that the bottom layer ($Z=1$) would encounter a higher rate of heating than internal layers, where the ceramic material would slow the diffusion of heat into the laminate. However, do the layers near the top (e.g. $Z=16$) have the slowest rate of heating because of their distance from the heat source? Or are they subject to an intermediate rate because of their proximity to the top surface of the laminate from which heat in the air could reach internal layers?

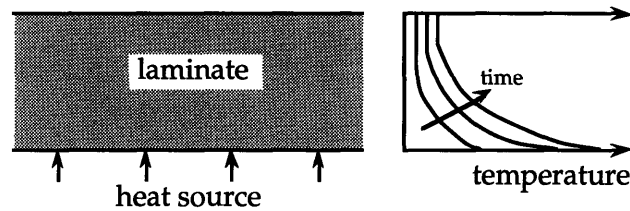


Figure 4.12a: Heating of laminate with the bottom heat source dominating the firing process. The temperature profile, also dependent upon time, is monotonic in behavior.

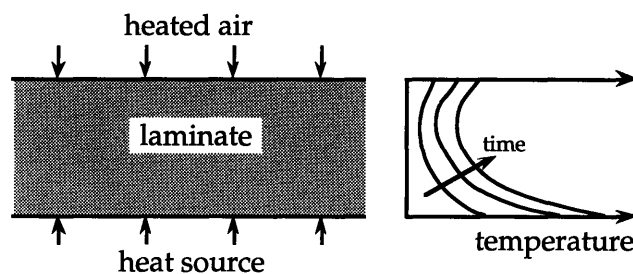


Figure 4.12b: Another heating profile from firing, considering both the bottom heat source and air heating the top of laminate. The temperature profile is quadratic in nature.

The former situation, shown in Figure 4.12a, heating from only the bottom of the laminate implies that temperature is monotonic with Z . For the latter situation, in Figure

4.12b, heating from the top and bottom surfaces during firing suggests a parabolic or quadratic temperature trend in Z .

In either case, quantitative model formulation begins with the analytical model of transient conduction in a semi-infinite solid which can be found in heat transfer references such as [Incropera, 1990] and [Mills, 1992]. The given temperature model is:

$$\frac{T(z,t) - T_i}{T_\infty - T_i} = \operatorname{erfc}\left(\frac{z}{2\sqrt{\alpha t}}\right) - \left[\exp\left(\frac{hz}{k} + \frac{h^2\alpha t}{k^2}\right)\right] \operatorname{erfc}\left(\frac{z}{2\sqrt{\alpha t}} + \frac{h\sqrt{\alpha t}}{k}\right) \quad (4.20)$$

where T_i and T_∞ are the initial surface temperature and heat source temperature, h and k are the convection and conductivity coefficients, α is the material thermal diffusivity, z is the distance into the laminate from the bottom surface, and t is time of heating. For the case with convection from the bottom and top surfaces, the model is approximated as the superposition of the analytic solution, bearing in mind that only a first-order model is desired.

Setting the left side of (4.20) equal to C_T , a threshold dimensionless temperature, meaning that the temperature $T(z,t)$ at location z at time t is, say, 95% of the characteristic temperature difference ($T_\infty - T_i$), and discerning from temperature history plots⁹ that (4.20) exhibits natural logarithm behavior, (4.20) is approximated as:

$$\ln C_T = a + b \ln\left(\frac{z}{2\sqrt{\alpha t}}\right) \quad (4.21)$$

with a and b characterizing the transformation. Solving for time t , (4.21) is reduced to:

$$t = K(z - z_0)^2 \quad (4.22)$$

where K incorporates the material and convection properties into a constant, and z_0 is a reference frame offset.

The variation in resistance from the resistance model is thought to be dependent upon the time to heat the laminate and resistor ink to a critical level. Thus, variation in resistance is postulated as:

$$F_{\text{heating}} = \frac{R_{\text{heating}}}{R_{\text{base}}} = C_1 + C_2 t \quad (4.23)$$

with C_1 and C_2 as hypothesized scaling and magnitude coefficients. Substituting (4.22) into (4.23) results in:

$$F_{\text{heating}} = K_1 + K_2 z + K_3 z^2 \quad (4.24)$$

where K_1 , K_2 and K_3 result from substitution and include other scaling concerns.

⁹ from [Incropera, 1990], page 261, for example.

(4.24) can be applied to either a one-side convective heating situation, as in Figure 4.12a, or for a two-sided process as in Figure 4.12b. The superposition of two equations of the form (4.24), one for each convective surface, can be approximated by the same form, again to first-order. The differences appear in the coefficients K_i , reflecting where the model extrema are located in the laminate. In the one-side convection case, the extremum is at the top, unheated surface, while for two-sided convection, the extremum is within the laminate.

Without considering the confounding with x and y , half of the inks demonstrated a monotonic trend (extremum at the surface) while the other inks showed a quadratic correlation (extremum within the laminate). Difficulty arises in interpreting the results not only because of the interdependence with other variables, but also because the dataset includes only measurements on four internal layers. For example, both a line and a curve can return favorable regression results when fitting to only four values in the Z domain. Like the mechanisms dependent on location on a layer, this mechanism has not been refuted, but similarly cannot be supported unequivocally.

Other mechanisms have been considered, but have not been adequately researched to introduce a quantitative model contribution. The following cases are some of the other effects which have been postulated but not yet quantified nor tested.

Nonlevel Squeegee Blade

This mechanism considers that the squeegee blade itself is not straight, due to nonuniform forces clamping the rubber blade and thus creating a nonlinear front-view profile. At locations of the blade which extend lower to the screen, pressure on the ink is decreased, and vice versa for higher portions of the blade. If the blade is held, for example, by bolts at discrete locations along the blade, then these areas are likely to be compressed. Considering deformation effects, these areas will manifest themselves as ripples along the squeegee.

Also, the ends of the blade will encounter less physical constraints, and thus will be freer to deform under the squeegee force than the middle of the blade, which is constrained on both ends.

Snap-Off Effects Versus Fabric Sticking

[Riemer, 1988b] describes two opposing physical effects: snap-off and fabric stick. In the beginning of a print stroke, the angle between the trailing mesh and the substrate is largest. This large snap-off angle causes the fabric to vertically spring back

as the squeegee passes, suggesting that ink is released less reliably at the start of a stroke than at the end of the stroke, where the snap-off angle is smallest and the screen springback is slowest.

However, another mechanism is fabric sticking, which counters some of the snap-off effect. At the end of the print stroke, there is a significant cling zone, an area where the screen is still in contact with the ink and substrate behind the squeegee. When the squeegee finishes its pass and is brought to the rest position (at a higher location than during printing), the screen in the cling zone can spring back too quickly and disrupt the proper ink deposition.

These two effects considered together would have a model contribution dependent upon the variable describing the print stroke direction, but this formulation has not yet been derived.

Resistor Orientation

Earlier references on screen printing such as [Hughes, 1967] show that the orientation of a resistor with respect to the print stroke direction has a sizable effect on the thickness, width and consistency of the print. When printing a resistor of high or low AR along its longer dimension, the thickness of the resistor is more consistent than when printing along the shorter dimension. The opposite holds true for the width of the printed resistor.

Referring back to Figures 4.2 and 4.3, it can be discerned that the orientation variable has been confounded with location (circuit or quadrant). Considering also the nonvariability of high AR resistor locales (they occupy the same relative locations in each row of resistors on each circuit and layer), this mechanism is difficult to evaluate.

Perimeter Oxidation Effects

Similar in nature to the topography mechanism, this mechanism considers the effects of oxidation of resistor material around the perimeter of the resistor. When the collated and stacked layers of printed substrate are laminated, the layer with resistors may not completely seal with the layer above it because of the nonzero thickness of the resistors and the lack of bonding material at the resistor-layer interface. Thus, there can be gaseous pockets or voids along the edges of the resistor, as these are the likely places where the layers do not meet. A different chemical reaction may occur at these locations, resulting in different material properties of resistors. This mechanism has also not been fully investigated.

4.4 Case Study Conclusions

During the course of research on the LTCC manufacturing system, it has been found that the screen printing process is still much of an art form rather than a scientifically-ordered activity. This case-study has demonstrated the complexity of the field and of the operations used to produce hybrid circuits. The research has also shown that an overwhelming majority of this manufacturing system has largely gone uninvestigated and provides a plethora of opportunities to which this methodology can be applied. This chapter closes with conclusions about the resistor analysis activities and future activities that directly follows the present state of research.

4.4.1 Process Understanding

LTCC production involves scientific fields ranging from material science to thermal design to fluid dynamics. The operation of resistor printing is similarly complex, and the mechanisms described in the previous sections only begin to address the possible sources of variation and error from a target resistance model.

This research confirms the first-order adherence to a physics-based model of resistance, and while the quantitative benefits of the analysis leaves much room for improvement, there are several leads that may uncover significant causes of variation from target that have so far escaped detection.

The mechanisms analyzed, if continually supported, provide continuous functions which allows for interpolation and extrapolation more believable than non-parametric techniques. By identifying the confounded nature of the original designed experiment relative to the mechanisms which need explaining, the analysis have indicated what the next sets of experiments should correct and include. Combined with the proposed mechanism investigations, critical parameters such as layer location and Z layer have gained importance.

As for gaining a more complete sense of the manufacturing system as a whole, the research has shown that LTCC production is a large enterprise which must address the real constraints of the company organizational structure without neglecting the scientific method of analysis and problem-solving. The practical experience of working on this project has provided valuable insight into the real working environment. Without this exposure, a modeling methodology might utterly fail when applied to actual production situations. By acknowledging and incorporating not only the many scientific fields but the managerial and social concerns as well, this methodology has been deemed eye-opening by the participants involved.

4.4.2 Future Analysis

While the methodology has been validated, the numerous mechanisms described in Section 4.3.5 show that there is still much research to be pursued. Some of this immediate work includes further analysis of the current dataset to determine if the data and the proposed mechanisms reveal any secondary effects not yet found. In the near future, another dataset is expected to be available for similar analysis, to reevaluate the results given in this case-study and also to enlarge the sample size for the testing of additional models.

Thus, the principle of continuous improvement may be employed by searching deeper into the specific problem of resistor printing and by broadening the scope of the operations modeled. This includes the investigation of the firing process, the preparation of machinery and material, and the effect of operator and environment on the output. With this thesis methodology, it is feasible that other engineers and analysts can work on the LTCC system simultaneously, independently or cooperatively with the author. Not only will this help the company and the general industry develop manufacturing modeling efforts, but will also provide more information whereas this methodology can be improved and refined.

Chapter 5

Conclusions & Future Work

This thesis is only the beginning of the author's attempts to provide a straightforward methodology that addresses the needs of real design and manufacturing enterprises in their pursuits of quality and efficiency. This final chapter summarizes the achievements of the research and proposes additional work that can be pursued.

5.1 Achievements of Thesis Work

There often exists a sizable barrier between research in academic institutions and the actual problems in the "real world" of production. Obstacles may arise because research makes assumptions for the purposes of simplicity, solvability, or to avoid logical or mathematical objections. Also, due to non-technical constraints in the workplace, even the best formulated tools and most robust practices may not be properly implemented.

In the design and manufacturing realm, there is the need for a methodology which bridges this gap, combining scientific principles with industry standards without endangering either the utility of the method or the normal activities of the company. This thesis work begins with the recognition of company issues, strengths and weaknesses, and applies commonly-used and well-accepted design, manufacturing and modeling principles. After only a year of cooperation, the work shows great potential in addressing the increasing demands of manufacturing enterprises. Similarly, the experience culminating thus far in this document highlights the benefits and importance

of basing engineering research with real engineering challenges. These achievements can be summarized with the following points:

- Technical and non-technical issues have been integrated into a modeling methodology.
- Both the managerial levels and separate analysis teams can implement the same methodology in different ways for a common purpose.
- The qualitative and quantitative modeling procedures are applicable to an unspecified range of applications in design and manufacturing.
- Additional university-industry cooperation can strengthen the methodology; both the academic and work settings can benefit from its application.

5.2 Future Endeavors

The case-study included in this thesis is only one of many possible manufacturing systems that can utilize the methodology. By investigating other industries and incorporating new concepts into manufacturing operation modeling techniques, the resulting methodology can become a widely-accepted tool in industry.

Future work may also include the development of worksheets and computer software packages that provide a user-friendly platform. This would make the design and manufacturing information, both qualitative and quantitative, available to any members in an enterprise needing those results. For example, the manufacturing constraints or optimal design windows could be stored on a database that design teams could consult for new product configurations. This cooperative tool would also centralize information and assist in documentation of the modeling activities. As additional data becomes available and as the manufacturing system evolves, the accomplishments up to that point would be easily accessible and locatable.

Tools of the methodology, such as the statistical and mathematical analysis tools, may be expanded and enhanced, possibly including nonlinear analysis packages. Other software packages, such as fluid flow and injection molding simulators, may be linked to analysis procedures to streamline modeling efforts.

In following the doctrine of continuous improvement, additional research should include efforts to improve the methodology and the tools it uses. In the broader sense, future endeavors should continue to foster the relationship between the scientific community and industry.

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