An Economic Analysis of Defect Flow and System-wide Surface Inspection at an Aluminum Rolling Facility

by
Jeffrey A. Wilke

B.S.E. Chemical Engineering,
Princeton University (1989)

Submitted to the Departments of Chemical Engineering
and the Sloan School of Management
in Partial Fulfillment of the Requirements for the Degrees of

Master of Science in Chemical Engineering
and
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Signature of Author ____________________
Department of Chemical Engineering
Department of Management Science
May 1993

Certified by ____________________
Jefferson Tester
Professor of Chemical Engineering
Thesis Supervisor

Certified by ____________________
Anantaram Balakrishnan
Associate Professor of Management
Thesis Supervisor

Accepted by ____________________
Jeffrey A. Barks
Associate Dean, Sloan Master's and Bachelor's Programs

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Abstract

This thesis, one product of a six-month internship at a major aluminum rolling facility, provides a methodology to aid in the system-wide optimization of surface-quality inspection. The analysis is based on Cost of Quality (COQ) Frameworks that include appraisal (testing), prevention (process improvement), and failure (internal and external) costs. In the short run, where major capital investments and labor costs are fixed, we do not address prevention costs explicitly, though a project's projected cost may be compared with a reduction in failure costs. Appraisal costs for surface quality are low at this location, so they are ignored. Thus, this particular analysis focuses on the Cost of Poor Surface Quality (COPSQ) at an aluminum rolling facility for process steps where accurate data was available.

Through a mathematical combination of test capability and defect generation rates, we can reassemble actual scrap data. A spreadsheet model utilizing these expressions was created and combined with an existing engineering cost model. The results predict the total COPSQ (failure costs) and the Opportunity Cost of Missed Inspection (OCMI) defined as the portion of COPSQ that could be eliminated given perfect inspection capability. Varying the inputs allows the user to predict the effect on COPSQ of producing fewer defects and of improving inspection capability. Reducing defects should always be preferred, at least in the long-run, to improving inspection, but we recognize that the movement toward defect minimization will require some inspection.

This thesis highlights specific observations and recommendations for an aluminum rolling process that may be generalizable to other industries and processes and provides some general learnings that came from working on an important business problem in a plant environment. The unique academic contribution of this thesis is its attempt to link COQ as a management tool to the underlying characteristics of defect generation and inspection.

Thesis Advisors:

Jefferson Tester,	Professor of Chemical Engineering
Anantaram Balakrishnan,	Associate Professor of Management

Acknowledgments

I would like to first thank the Leaders For Manufacturing Program, including its industrial partners, the Sloan School, and the Department of Chemical Engineering for investing significant resources in a program that may change the course of American industry forever. I am indebted to the intellects and hearts of those who truly believe that manufacturing provides the only sustainable growth in the standard of living of human beings. This growth has become my passion, and I am extremely pleased to have found a group of institutions and people that share this energy.

I am very grateful to the people of the plant where I spent my internship, including all of the members of the Recovery Lead Team.

I could not have completed the thesis in its final form without the attention and support of my Sloan advisor Anant Balakrishnan and my Chemical Engineering advisor Jeff Tester. I gained from them a deep appreciation for the considerable task of constructing academic writings and learned a bit more about my own bias toward verbosity.

My peers at LFM are without equal. They have enriched my life in more ways than I can possibly enumerate. I sincerely hope that over the course of our lives, we continue to support one another as we have for the last two years.

Finally, I would like to express my undying love and devotion to my wife Liesl. We have so far approached our life together as a team. I hope that we'll always do it that way!

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Chapter 1 -- Introduction and Business Overview

1.1 Thesis Highlights

This thesis, one product of a six-month internship at a major aluminum rolling facility of the National Aluminum Company (NAC), provides a framework for both *descriptive* and *predictive* analysis of plant-wide surface inspection. The analysis does not suggest that inspection is a substitute for reducing process variability. However, given an environment that contains significant process variability, the analysis recognizes that inspection plays a role in ensuring customer satisfaction and cost minimization.

This work provides a methodology to aid in the system-wide optimization of surface-quality inspection. The analysis is based on Cost of Quality (COQ) Frameworks that include appraisal (testing), prevention (process improvement), and failure (internal and external) costs. In the short run, where major capital investments and labor costs are fixed, we do not address prevention costs explicitly, though a project's projected cost may be compared with a reduction in failure costs. Appraisal costs for surface quality are low at this location, so they are ignored. Thus, this particular analysis focuses on the Cost of Poor Surface Quality (COPSQ) at an aluminum rolling facility for process steps where accurate data was available.

Through a mathematical combination of test capability and defect generation rates, we can reassemble actual scrap data. A spreadsheet model utilizing these expressions was created and combined with an existing engineering cost model. The results predict the total COPSQ (failure costs) and the Opportunity Cost of Missed Inspection (OCMI) defined as the portion of COPSQ that could be eliminated given perfect inspection capability. Varying the inputs allows the user to predict the effect on COPSQ of:

1) producing fewer defects
2) improving inspection capability

Reducing defects should always be preferred, at least in the long-run, to improving inspection, but we recognize that the movement toward defect minimization will require some inspection.

This thesis highlights two outcomes of the internship project. The first is a set of specific observations and recommendations for an aluminum rolling process that may be generalizable to other industries and processes, including:

i) Changes in inspection location and frequency

ii) Changes in the focus and use of plant Information Systems

iii) General observations regarding the use of Cost of Quality systems in manufacturing locations including:

    a) Simple systems reporting out-of-pocket expenses for failures can dramatically alter perceptions
    b) COQ should incorporate external (at the customer) failure costs as these may be significant
    c) External failure costs should include the cost of processing (including customer costs), transportation, and additional sales/marketing time, and they should attempt to value the impact of current quality on future purchasing decisions
    d) Management should ensure that relative costs lead to reasonable relative decisions

In addition, this work highlights some general learnings that came from working on an important business problem in a plant environment. Such learnings include:

iv) The system-wide perspective can be achieved best by a team focus on the development and monitoring of key metrics. Such a team should have members from all production departments as well as sales and quality assurance functions.

v) Management must ensure that non-financial indicators chosen for ease of understanding do not contradict the financial objectives of the organization.

vi) Inspection, Quality, and Cost Systems must adapt to today's changing business environment including inventory reduction, increasing domestic and global competition, and new organizational structures.

The unique academic contribution of this thesis is its attempt to link COQ as a management tool to the underlying characteristics of defect generation and inspection.

1.2 Road map Through Thesis

The thesis is organized into chapters that present general background and process information, discuss relevant theories and literature, and conclude with site-specific and more general recommendations based on a model presented in the middle chapters. The chapters are constructed as reasonably encapsulated topics that should interest readers from a variety of viewpoints. The remainder of Chapter 1 contains an overview of the Rivertown Operations, its business challenges, and the impact of NAC's Step Change effort on the plant. Chapter 2 presents the detailed objectives of this thesis that emerged from an initial problem statement provided by the Recovery Lead Team, a group of plant superintendents attempting to improve process yield. It also includes a description of the Rivertown production process and current inspection system, as well as the approach used to address the objectives. Chapter 3 summarizes the background material by reviewing some of the existing COQ and inspection optimization literature.

Chapter 4 introduces some of the specific issues surrounding COQ at Rivertown. It also contains definitions, descriptions, and mathematics of the particular framework utilized for the analysis at Rivertown. Chapter 5 places the model from Chapter 4 in a more general methodology for inspection system optimization.

Chapter 6 presents the details of the observations and recommendations highlighted earlier. Finally, Chapter 7 suggests some directions for future research.

1.3 Internship Project Context

The following sections describe the plant and business environments in which the model in this thesis was developed. Section 1.3.1 describes the evolution of the Rivertown plant over the last thirty years. Section 1.3.2 highlights the business challenges faced by Rivertown in 1992. Section 1.3.3 places the issues at Rivertown into perspective given corporate NAC initiatives.

1.3.1 Rivertown Overview

NAC decided to build the Rivertown Operations in the early 1950's. The geographic location's abundant land and coal provided a strong base on which to build a developing business. With steel being the major metal at the time for beverage and food cans, the enormous capital at Rivertown represented "...one of the most important investments NAC (had) ever undertaken to stimulate and expand the volume use of aluminum." [NAC president in 1964, in Saiko, 1991]

By 1964, Rivertown was producing fabricated products in the extremely vertically integrated plant. With a wholly-owned subsidiary generating required electric power, the 300-acre plant site now includes six smelting potlines, the world's largest aluminum ingot plant, rolling mills to reduce the 21-inch thick ingots to coils, and finishing capability that includes lubrication, polymer coating, and final width trimming. The plant employees over 2,000 people, most of whom belong to the Aluminum, Brick, and Glass Workers International Union. [Saiko, 1991]

Rivertown produces pure aluminum in liquid form, ingots of various alloys, a small number of thick (hot mill gauge) coils to be rolled by the customer to a smaller gauge, and millions of pounds of light gauge aluminum coils per year. These coils serve the beer, soft drink, petroleum, food, and consumer products packaging industries. With various sheet widths, gauges, coatings, alloys, and coil diameters, the actual possible product combinations number into the thousands. Rivertown is a strong competitor serving many of the aluminum can-makers worldwide and is looking forward to thriving well into the 21st century.

1.3.2 Rivertown's Business Challenges

By the end of 1992, the NAC Rivertown Operations was undergoing enormous changes in its external business and internal operating climates. Increasing domestic and foreign competition had driven margins down while forcing acceptable quality levels to all-time highs. Industry over-capacity had grown to nearly 30%, so much that Rivertown itself could close, and the industry would still be able to meet market demand.

With some of its capital nearly 25 years old and extremely inflexible, Rivertown was at times hard pressed to meet customer needs in an efficient manner. The variability and limitations of existing equipment in the plant began to surface rather audaciously with increasing customer comments on surface defects like rolled-in-dirt, scratches, and oil stains. Long changeover times and substantial work in process and finished goods inventory led to relatively slow response times and sub-optimal cost structures.

However, Rivertown does maintain some significant competitive advantages in the industry. With onsite power generation, smelting, and recycling activities, it is extremely vertically integrated. Several of the processes are unique to NAC, providing processing capabilities and throughput that greatly exceed those of competitors. Rivertown's survival depends critically on leveraging these advantages through the business transition from a revenue-based monopoly toward a quality and efficiency based competitive leader.

1.3.3 Step Change Efforts at NAC and Rivertown

In 1991, NAC's President instituted a program called "Step Change", an attempt to go beyond continuous improvement toward quantum jumps in process capability and competitive advantage. He asked each business unit to identify major strategic non-financial indicators on which plant performance would be evaluated. The goal was to focus efforts of operations personnel during a two year period on projects that would allow NAC to retain its leadership position in the increasingly competitive aluminum industry.

The Step Change goals at Rivertown, in safety, flowtime, recovery, and costs, could in fact provide the necessary leverage for the desired positive change. Safety measures the safety of all employees and visitors to Rivertown Operations. Flowtime is the time from ingot casting to shipment of the finished coil. As constraint management theories suggest [Goldratt, 1992], this time is governed by such parameters as inventory levels, process variability, plant layout, and product mix. Recovery represents the ratio of good metal that leaves a process to the good metal that enters it. Finally, the cost Step Change governs the reduction of standard accounting costs.

Safety forms an umbrella over all of the plant's operating and strategic objectives. Recent safety performance has been exceptional, and attention to safety details by plant personnel is obvious in every possible way. In fact, the plant has published a safety policy in which it pledges that nothing will come before safety, even if it means that the plant loses money.

The other goals are interrelated if we model the plant objectives as: maximize revenue minus costs subject to safety (of employees, the environment, and the community) and customer satisfaction. Note that safety and customer satisfaction must be satisfied (they are constraints) and costs appear explicitly. Flowtime and recovery enter in through the objective function. They are the means by which the plant can increase revenue and reduce costs on its way to industry dominance.

The Flowtime Team has focused its attention on improving order taking and scheduling and on inventory reduction. In one year, inventory levels have gone down by 50%. Such initial gains are not uncommon for an inventory reduction effort in a plant that traditionally focused on maintaining large inventories to meet customer orders. The real challenge lies ahead as the current reduced inventory reveals opportunities to improve processes, scheduling, and customer relations.

The Recovery Team, which sponsored the efforts of this thesis, has focused to date on increasing Recovery through revising and enforcing Standard Operating Procedures (SOPs) that minimize scrap, focusing on interdepartmental practices that can contribute to high scrap rates, and reducing the variability of the process. This variability takes on two components. One is the random variability introduced by the operating environment in the plant. The other relates to the inherent variability of the machines and procedures used to produce metal in the plant. Both of these sources have been questioned by recent teams and many valuable projects have commenced.

The Recovery projects include things as simple as padding metal trays that hold coils. Perhaps in this case, as with many of the simple fixes, increasing employee awareness of the sensitivity of the product to deformation can bring significant gains in recovery. More complex projects involve process control in areas like rolling lubricants and finishing polymer coatings. Interdepartmental projects that reduce incentives to sub-optimize overall results by optimizing individual ones have also brought impressive results.

Reducing variability through better process understanding and control (automatic and SPC based) is quite a challenge, but will be the highest leverage activity that the plant can possibly undertake. With reduced variability, the plant can reduce inventory and flowtime, increase recovery, decrease costs, improve customer satisfaction, and, bottom line, improve plant profitability.

Chapter 2 -- Internship Project Objectives, Current Production System, and Approach

2.1 Objectives -- Key Elements of Problem Statement

The Recovery Lead Team (RLT), with its stated charge of reducing internal scrap and implicit charge of improving visible quality to the customer, sponsored this analysis of the plantwide surface inspection system. The RLT prepared a project problem statement in June 1992 which is shown below. This section, focusing on the italicized phrases, highlights the objectives, information systems implications, and organizational changes imbedded in this problem statement. Section 2.2 describes the process flow at Rivertown.

Project Problem Statement

> Under the Step Change goals, recovery efforts have focused on departmental specific improvements and Recovery Lead Team efforts to identify and resolve systemic (across departments) problems. A major system wide issue, which directly affects Rivertown's ability to "maintain-the-gains" in quality and recovery, involves sampling and feedback of ***surface quality*** information. Recent occurrences (including a Hot Mill roll mark, Cold Mill roll mark and rolled-in dirt) clearly shows the present systems for sampling/evaluating are inadequate resulting in major field issues, ***loss of customer confidence*** and negative ***recovery impact***.
>
> Ideally, the system for surface quality sampling and evaluation must provide ***high confidence and timely information***, to ***appropriate personnel***, about surface quality performance. The information should be linked to (or used to assess) process variability whenever possible. This system must also trend quality performance, over time, and provide for ***periodic "audits"*** to assess long term system performance.
>
> Any work on sampling and inspection must recognize that the plant faces a dynamic marketplace (characterized by increasing competitiveness) and a dynamic production environment (moving toward reduced flowtime). The sampling system must be robust in optimizing customer satisfaction throughout these changes.

2.1.1 Problem Statement Objectives

Loss of Customer Confidence is a key issue leading to lost orders, increasing frequency of customer complaints, and poor treatment by the popular business press. One might argue that customer concern tends to parallel negotiations, presumably to obtain a lower price for a fixed contract. The fact remains, however, that customers were becoming increasingly concerned with the quality of NAC metal.

The element of quality typically of most concern is *Surface Quality*. Though other dimensions of product quality including composition, dimensional tolerances, and strength exist and are important, visible surface defects are most easily seen and, hence, tend to cause the most dis-satisfaction for customers. Such defects include foreign objects rolled into the sheet like dirt, aluminum slivers, steel from process machinery, and other contaminants. Polymer coating defects that appear as voids when under-weight or slings (affectionately known as "goobers") when over-weight are another class of examples. In fact, this work contains many examples of particular surface defects, from a variety of physical causes, that share one common characteristic: they are visible imperfections in the end product's surface.

Another important element of the problem statement is *Recovery Impact*. It reminds the reader that surface defects form a significant portion of unplanned scrap, both in the plant and at customer locations. Any reduction in surface defects will have a positive impact on the Step Change goal of recovery.

The Cost of Poor Surface Quality (COPSQ) framework to be presented combines all of these objectives into a useful management decision tool. With careful design and implementation of improvement projects (including taking into account the cost of such projects), reducing COPSQ will lead to higher recovery (of value) and better surface quality at the customer.

2.1.2 Problem Statement Implications for Information Systems

The phrase *High Quality Information* implies data that is accurate, appropriate, and timely for use in making production decisions. The team realized that minimizing surface defects would require much more than a plant-wide mandate to reduce defects. It would, to be successful, demand modification in the use of information by all levels of plant management. By the end of the six month internship at Rivertown, the team identified important changes in the developing Recovery Information System, current Production Tracking System (for scrap), and Cost Accounting systems that would support the objectives identified above.

2.1.3 Problem Statement Implications for Organizational Systems

The final set of key phrases from the original problem statement focus on the organizational impact of a system-wide surface quality effort. First, the information from the previous section must be communicated to *Appropriate Personnel*. I spent a considerable amount of time during the internship seeking out and discussing surface quality with a variety of "experts" in the plant. These people included Quality Assurance "experts" that had, up until 1989, spent all of their time inspecting product on the line. Management at that time decided that "inspecting in quality" was the wrong thing to do, so the experts were reassigned to more staff-like positions. One problem with this reassignment was that the knowledge that the experts possessed was not systematically transferred to the people who became responsible for quality: the line workers.

Other quality experts in the plant included sales and support people typically involved directly with customer problems. These individuals possessed tremendous ability to trace surface defects all the way from the customer problem back to an in-plant root cause. Most communication with the internal production people was typically funneled through the quality experts mentioned above.

All of the experts were heavily involved in identifying and solving surface quality problems, however, their efforts were somewhat uncoordinated and occasionally disconnected. As a result, this work focused on the development of a common framework and data set to tie together all of the quality efforts.

Next, the problem statement mentions *Audits and Trends*. These would be a logical outcome of a common framework and vision for the surface quality problem and should certainly be key elements of a plantwide surface quality inspection system.

Finally, the statement suggests that the effort to improve surface quality to the customer must be robust to changes in internal and external conditions. Examples of changing internal conditions include: reduced inventory and flowtimes, more self-directed work teams, and process flow changes. External conditions impacting surface quality include increasing customer expectations and ability to identify defects, enhanced capability of competitors, and down-gauging of metal thickness.

A team focused entirely on Surface Quality Issues will ensure the coordination of all of these concerns. Such a team, comprised of members of each of the groups mentioned above, could:

i) develop effective standards for monitoring surface quality and making sell/scrap decisions

ii) improve the accuracy and usefulness of information used to make quality decisions

iii) ensure that a consistent and system-wide approach is taken to improve surface quality in a fashion robust to changing conditions

2.1.4 The Problem Statement and Inspection

Though optimizing the surface quality inspection system forms the primary objective of this thesis, the key elements of the problem statement that are also necessary for the reduction of variability in process and product were emphasized in earlier discussions to place proper perspective on the focus of the thesis. In fact, if the plant moves toward zero process variability, the need to inspect to assure quality will diminish.

Though zero defects provides an important theoretical limit, it is not possible given current equipment and less-than-limitless capital resources. In this case, we must turn to inspection in order to minimize the impact of poor surface quality at the customer and to reduce internal scrap costs. If we are going to set up an infrastructure to do this, however, we should create one that can also facilitate variability reduction.

2.2 Rivertown Production Process Flow and Surface Inspection Locations

Though the Rivertown Operations include process steps from smelting and power generation through recycling, this study of surface quality will focus primarily on the fabrication process in ingot casting through finishing (coating or lubrication.) This is the area of responsibility of the Recovery Lead Team and includes the processing steps most directly related to surface quality. Note that the process flow described below, coupled with the chemical composition of the cast metal, determines the specific nature of the product. Rivertown produces three main alloys (one for beverage tabs, one for the side of a can, and one for the top), with or without polymer coating, in a variety of coil widths, coil lengths, and gauges. The process can be characterized as high-volume with relatively few product families. Within these families, a large number of ultimate product varieties are possible.

Figure 2-1 shows an overall flowsheet of the process in this plant. The dotted lines separate the four major fabricating departments: Ingot, Hot Mill, Cold Mill, and Finishing. Production employees, engineering, and support services are structured directly or loosely around these departmental divisions. The sequential blocks within fabricating departments form the basis for the COPSQ model presented here.

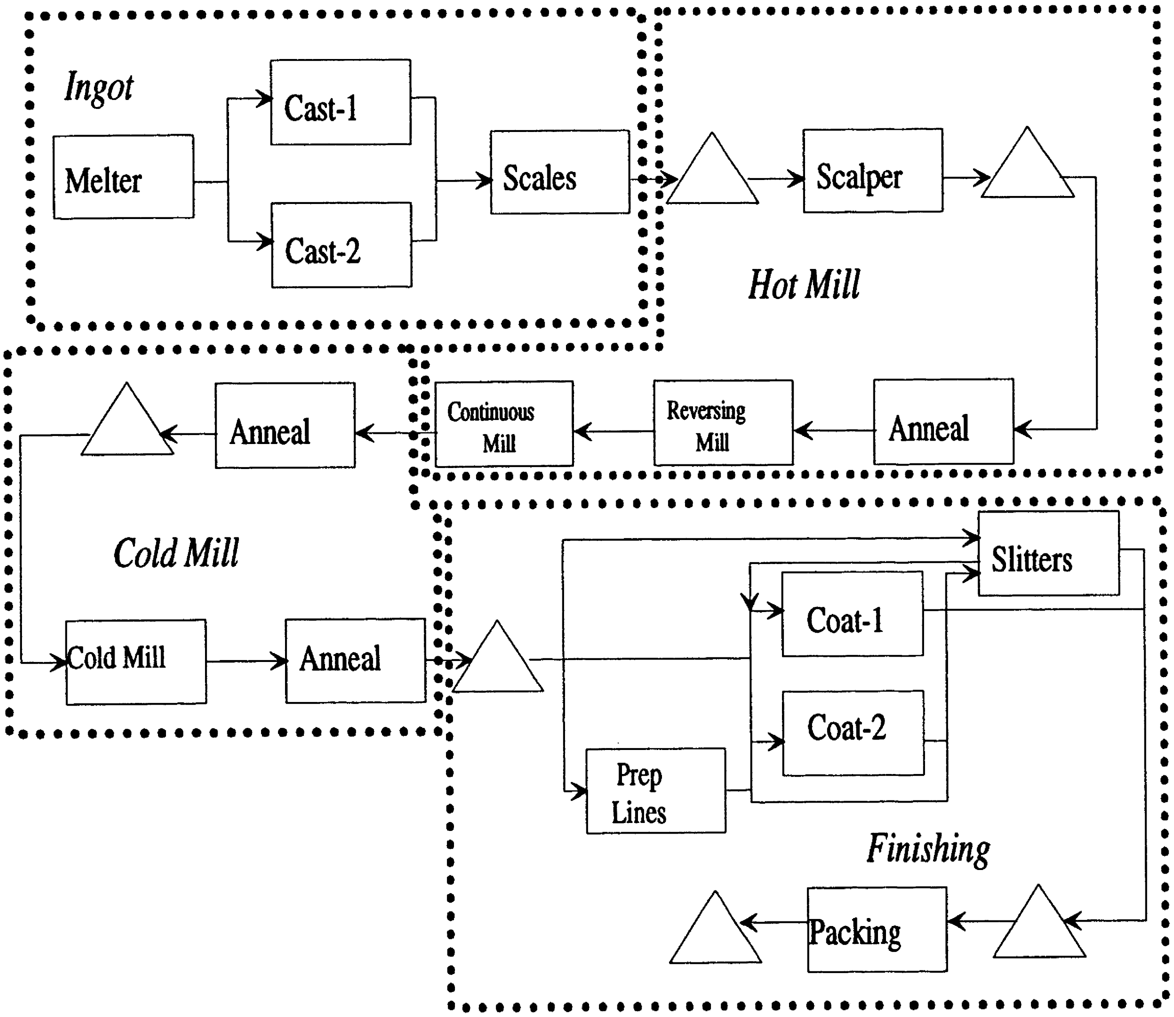


Figure 2-1. Process Flowsheet

Figure 2-2 shows the product dimensions and lot form as the aluminum moves from the Ingot plant through Finishing.

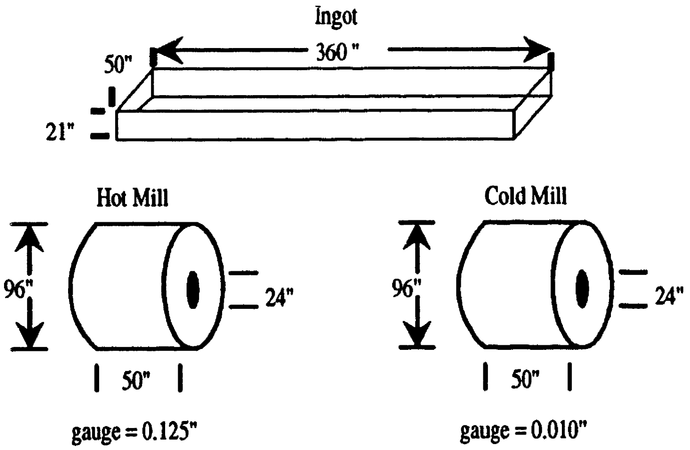


Figure 2-2. Product Dimensions Throughout Process

2.2.1 Ingot

The ingot plant consists of two Cast-1 pits and four Cast-2 pits. These pits cast ingots up to 360 inches long weighing well over 30,000 pounds. Though the physics and quality of the ingots from the two types of casting units are different, their basic purpose is the same. The ingot plant is where raw aluminum, from internal or outside smelters or from cleaned recycled aluminum cans (up to 60%), is combined with alloying elements like zinc, manganese, magnesium, or iron in melters to produce the final metal solution that the customer desires.

Note that the alloy and casting conditions (called "casting practice") are two of several parameters that determine the ultimate product characteristics. The microstructure, surface composition, and quality of the metal are influenced by rolling and Finishing processing as well.

The key value added in the ingot casting step is the ability to optimize the width of the finished coil (since the rolling processes cause very little expansion in the direction perpendicular to the rolling force), the alloying mentioned above, and the creation of a dense single "lot" that can be stored and moved by crane to rolling machines. Surface inspection here is limited to the observation of gross defects by workers and supervisors throughout the department.

2.2.2 Hot Mill

The Hot Mill process formally begins just after ingots are weighed. The scalping area removes the layer of oxide and transient metal solution from the top and bottom surfaces of the ingot in an operation that resembles traditional milling. From the scalper, the ingots move to annealing furnaces that bring the ingots up to a temperature over 700 degrees Fahrenheit to remove the residual stresses caused by the casting and scalping processes from the microstructure of the material. The entire annealing process can last for most of a day. Even with over 30 furnaces this step can limit production activities due to its long times.

After removal from the annealing furnaces, ingots must be quickly moved to the reversing mill (shown in Figure 2-3) before they cool down enough to a point where the metal won't flow under the stresses of rolling.

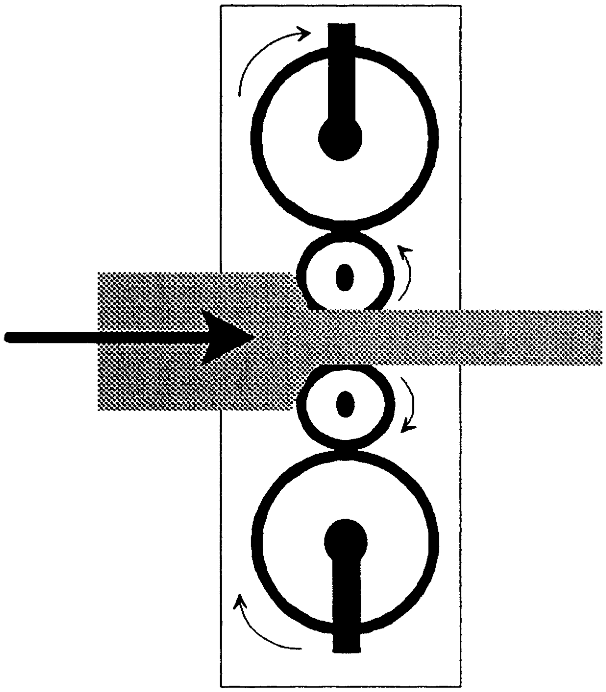


Figure 2-3. Single Stand Reversing Mill

As Figure 2-3 illustrates, the reversing mill consists of four rolls. Two small work rolls contact the metal (and accomplish the reduction in thickness) while two larger rolls maintain pressure on the work rolls. These rolls are larger to reduce warping of the work rolls through consistent application of force across the entire roll surface. Several passes through the reversing mill are required to reduce the metal thickness to the correct gauge for the next step. Note that the temperature of the metal increases here due to the internal work of rolling.

The continuous mill accepts the slab from the reversing mill and, through a series of stands (each resembling the reversing mill stand described above), reduces the metal in the final step to a thickness of about 1/8". It is after this step that the metal is first moved in the from of a coil.

Sampling at the Hot Mill is done several times per shift in the form of a "5-Stand Test" and at the exit end of the continuous mill. The 5-Stand Test consists of running a slab through 5 of the 6 continuous mill stands. When the slab is stopped, one can see the progressive reduction in the metal thickness over a 40 feet long sample (see Figure 2-4).

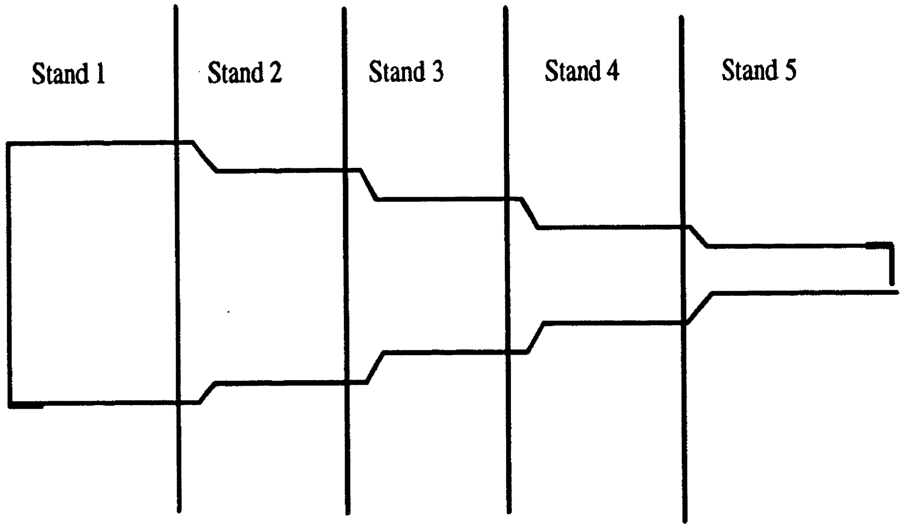


Figure 2-4. 5-Stand Sample

Problems attributable to any of the first five roll sets are visible as are general surface quality defects. The continuous mill sample consists of a variety of dimensional measurements and a surface grading that utilizes a chemical wash to remove the surface "glare" and aid in the identification of oxide and dirt "pick-up" on the sheet.

As a result of Hot Mill processing, which changes the microstructure through the rolling operation, the product becomes stronger, yet more malleable, and the surface becomes shinier.

2.2.3 Cold Mill

The three cold mills transform the microstructure to close to its final coiled form. These cold mills differ in their processing speeds, thickness reduction capabilities, and widths, however they all operate in roughly the same fashion, similar to the continuous mill in the Hot Mill department. Sequential stands (five or six) reduce the metal to gauges below 0.020 inches.

Surface inspection occurs regularly at the exit end of the cold mills. At a standard frequency, several "wraps" of metal are examined from the outside of the coil. In addition, an occasional "super sample" is taken which allows the inspector to look at metal that is "into the coil".

The primary value added to the product in the Cold Mill is the reduction of metal thickness to a very precise final gauge and the altering of the microstructure and surface, giving strength and appearance attributes to satisfy the customer's demands.

2.2.4 Finishing

The Finishing area includes more processing centers than any other department. The two Coat-1 lines, one Coat-2 line, six slitters, and four prep lines all prepare the bare metal sheet for use by the customer. As the detailed flowsheet in Figure 2-1 indicates, there are many process pathways through this portion of the plant. The coating lines level the sheet (remove minor wrinkles in thickness), wash it, apply a polymer coating, and lightly lubricate the sheet. Only products that require a coating before going to the customer site follow this route. Such products include metal used for some pull tabs, food cans, and the ends of beer and soft drink cans.

Drawn and Ironed metal (D&I) to be used for the body of beer and soft drink cans goes through prep lines and/or slitters. The prep lines function much like the coating lines but do not apply a polymer coating. Slitters cut the coil into coils of smaller width. As much tab stock is sold in final width, there are slitters that can cut a coil into as many as 20 smaller coils.

Sampling in the Finishing area is done primarily at the exit end of the prep and coating lines. With frequency and number of feet varying by machine, operators observe the surface quality and send samples of every sheet to a laboratory for chemical and mechanical testing prior to shipment to the can-making customer.

2.3 Other (non-surface) Inspection

The four surface inspection sites at the Rivertown plant mentioned above (5-Stand, continuous mill, cold mill exit, and finishing exit) plus visual inspection by the customer represent the primary inspection points to assess the surface quality of Rivertown metal. Note that none of the manual sampling inspects all of a sheet. In fact, most of the sampling inspects only the ends of the sheet: one end in the Hot Mill, the other end in Cold Mill (since there is a wind and unwind step in between) and finally the first end again in Finishing. Some repeating defects related to failure modes in the process and many random defects are not identified with this procedure, hence there is an obvious opportunity for improving inspection.

In addition to surface sampling and inspection, the current quality monitoring effort involves automatic and statistical process control, chemical tests, and mechanical properties tests. Process control of mill speed and force and most casting and preheat practices are completely automatic. Coat-2 itself has over 60 variables that are controlled by programmable logic controllers (PLCs). Operators and supervisors monitor other controllable variables throughout the plant including lubricant/coolant temperature, viscosity, and composition; sheet washing process temperature, concentration, contact times, conductivity, ion activity, and spray volumetric flow.

An onsite Quality Assurance Laboratory tests coating weight, lubrication weight, color, physical properties (yield strength, elongation, tensile strength, and gauge), and surface treatments. All of these properties must conform to specifications received from the customers.

These tests and inspections combine to ensure that the customer receives good quality metal. But, as recent complaints indicate, the inspection process is far from perfect and will be even less so if Rivertown operations does not keep pace with the increasing expectations of their customers in regard to surface quality.

2.4 Approach to Surface Quality Problem

With the support of the Recovery Lead Team, we took the following approach to address the problem statement provided by the team:

1) Understand the process, the types and causes of surface defects, and the current efforts to address them.

2) Interview as many of the people involved in the quality effort as possible. Understand their objectives, motivations, and current work.

3) Develop a COPSQ framework for implementation as soon as possible.

4) Tie the objective of reducing COPSQ to the test capability and defect generation rates at individual processing centers to allow optimization of inspection frequency and location as well as identification of the most expensive defects.

5) Begin to educate as many people as possible about the benefits of a

coordinated surface quality effort with COPSQ as its driving metric.

2.4.1 Conceptual Model of Surface Inspection System and Defect Flow

We could model each piece of the Rivertown process described in the previous section as a black box with inputs and outputs, sensors, actuators, and controllers. In such a model, the whole plant consists of interconnected groups of such blocks. Figure 2-5 shows one representation of the Hot Mill using a block diagram that is useful for illustrating the importance of variability and its relationship to the inspection system.

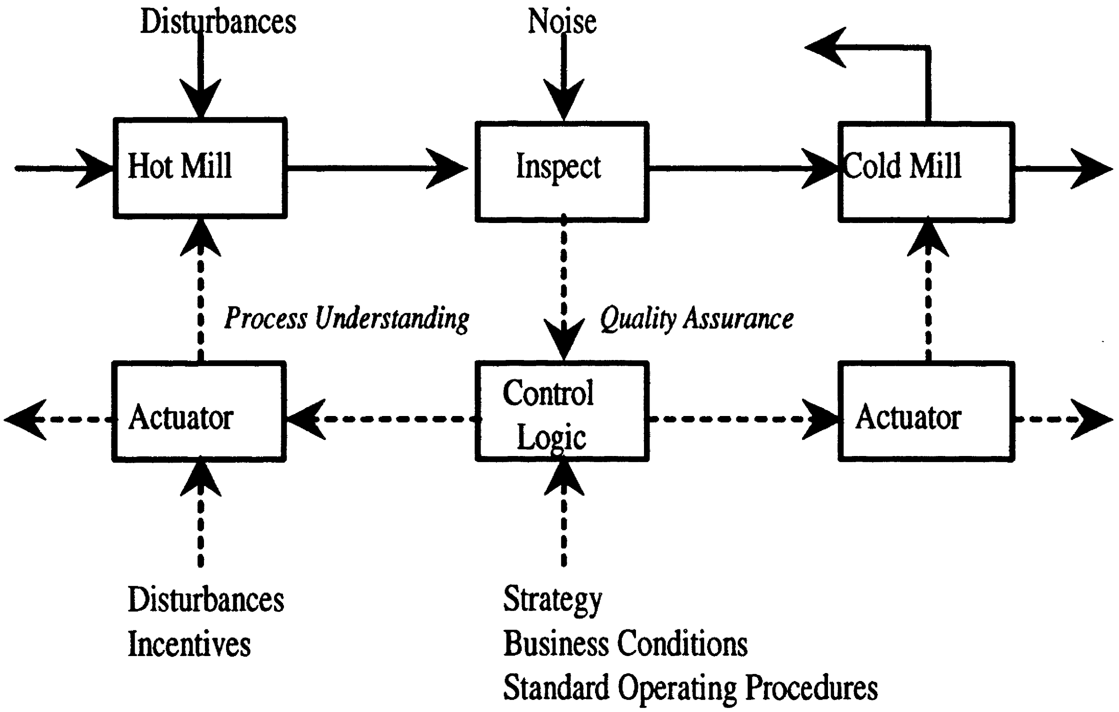


Figure 2-5. Feedback Representation of Process

As this figure illustrates, disturbances into a large system come from a variety of sources. Direct disturbances to the Hot Mill itself include lubricant temperature perturbations, roll pressure changes, metal inconsistency, human error, and changes in ambient conditions. Sensor noise exists in electronic gauge sensors as well as in the human eye. Business strategies, external business conditions, standard operating procedures, incentive plans and other external forces influence human behavior. In addition, as Peter Senge suggests in the Fifth Discipline [Senge, 1990], mental models of situations and behavior influence behavior and reactions. Computer controllers always contain errors or simplifications in the models they use reducing their ability to accurately react to a perceived problem. Finally, actuators, either machine-driven as in valves or relays, or manual as in knobs, buttons, dials, etc. are subject to a variety of mechanical and sensitivity errors.

The goal of reducing surface defects that get to the customer requires the plant to work on understanding and reducing all sources of variability. While this process control work is going on, the inspection system should be constructed to minimize the costs of defects that are generated.

Using Figure 2-5, one can begin to list the information and data required to complete the five steps outlined in the above approach. First, however, some clarification and definition will aid understanding.

The solid arrows represent the actual flow of metal through process steps. Arrows pointing to the right represent metal with increasing value added. Left-pointing arrows represent recycle or scrap streams. The dashed arrows represent information flow in this system. Though the boxes may have multiple pieces of hardware, software, or human systems within them, the production systems do have information linkages that appear very similar to those in the diagram. Here, we define *Quality Assurance* or "Inspecting in Quality" as information passed downstream to identify defects before they get to another value-added step or are sent to the customer. *Process Understanding* is defined as the use of information to adjust upstream processes to eliminate or reduce the frequency of defect generation.

Only through Process Understanding can we achieve the variability reduction necessary in the long term for flowtime reduction, recovery improvement, and profit maximization. Process Understanding takes on a variety of forms, but is certainly aided by the accurate and regular inspection of product. Every machine center from an inspection site upstream can learn from the data gathered during sampling. In addition to identifying and reducing sensitivity to disturbances, Process Understanding can lead to better process control (through better physical modeling), better reactions to different inputs (like product mixes), and improved interactions of whole departments when the arrows carry information outside the boundaries of the department that generated the information.

Thus, inspection for Quality Assurance plays an important role in minimizing costs and providing important information for long-term Process Understanding. In fact, a central tenant of this thesis is that:

> *We must optimize Quality Assurance as we continually work on Process Understanding to reduce variability. The long-term goal of everyone, though, should be to minimize inspection as a means to improve quality.*

2.4.2 Understanding Data Requirements for a COPSQ Model

As the approach outlined in the beginning of this section emphasizes, any work of this sort should attempt to understand as many of the solid and dashed arrows (referring to Figure 2-5) as possible. Previous sections gave some information regarding the physical and managerial processes in the plant. This section will focus on the key data necessary to create a "report card" of surface quality inspection performance and to model this system in a meaningful fashion.

As our goal is to reduce the amount of defective metal that gets out of the last solid arrow (Finishing in the Rivertown process), we should understand the amount of metal that flows through all of the solid arrows in the process. For whatever economic framework we wish to use (here it will be COQ) we should understand the value added through each step in the process.

Taking a "short-term" view of the inspection process, that is, that we assume that

Process Understanding is an ongoing effort, we can take the actuator/control logic portion of Figure 2-5 as fixed. In that case, then, we can roll the dashed arrows into the top line of black boxes. This creates a simpler conceptual model like the one shown in Figure 2-6 below.

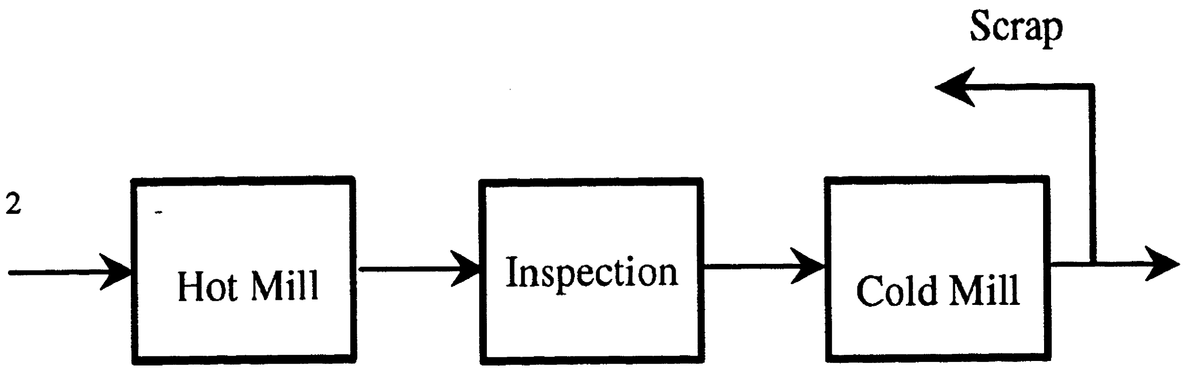


Figure 2-6. Sample Block Diagram for Economic Analysis

Now, one can break down the data encapsulated in each lot of metal flowing through the solid arrows into several components:

i) the amount of metal flowing in the lot

ii) the chance that the metal gets a defect of any type in moving through a black box

iii) the chance that a sensor box notices any defect

With this information and some assumptions about interactions between steps, an economic framework can be developed to describe the "dollar flow" of defects through the plant and predict how that flow might change given changes in the underlying data. This is the subject of Chapter 4.

Chapter 3 -- Review of Theory and Critical Issues

3.1 Quality and Cost of Quality Literature Survey

Beginning with brief summaries of the views of two very influential quality experts, Deming and Juran, this section moves toward an understanding of the limitations and uses of Cost of Quality analysis. The key points that the literature seem to emphasize are:

1) Quality Costs go to zero when variability is removed from the process.
2) Any COQ system should be kept relatively simple.
3) COQ can fit in with other organizational and economic objectives.

3.1.1 Deming's Views on Quality

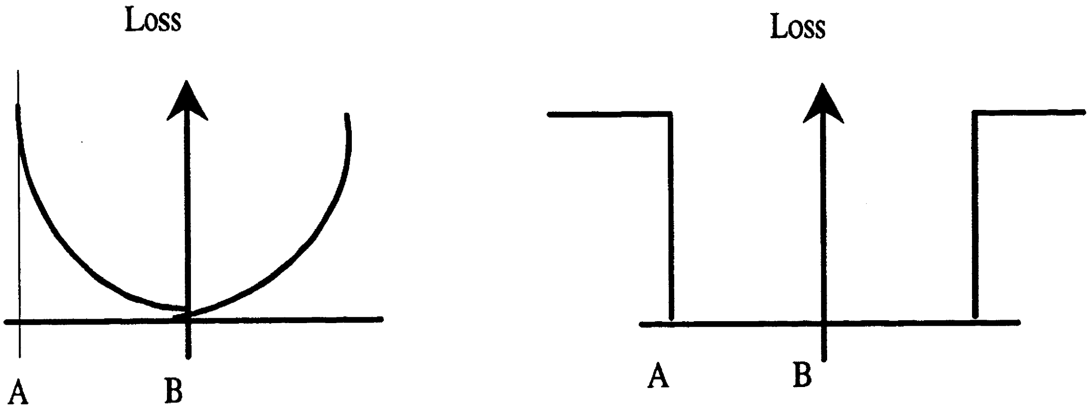
W. Edwards Deming believes that one cannot assign costs to quality. [internal White Paper, 1992] In the sense that Quality Costing may typically institutionalize the inspection process, this violates a key principle of Deming's:

> Detection of defects, even with the use of sophisticated technology, is not a viable competitive strategy in this new economic age. [Scherkenbach, 1988]

Deming asks organizations to cease dependence on inspection to achieve quality. Rather, management and workers alike should look for ways to build quality into the product in the first place. [Scherkenbach, 1988]

Deming's route to variability reduction involves the strategic implementation of continuous improvement. Utilizing quality tools like control charts, Ishakawa (Fishbone) diagrams, scatter plots, and Pareto charts, groups can turn the Plan/Do/Check/Act wheel toward competitive advantage. [Scherkenbach, 1988]

In addition to in-depth descriptions of various quality tools and frameworks, Deming typically shows employees new ways of looking at old data. For instance, he advocates the movement away from step loss functions toward more realistic (parabolic for instance) continuous functions. Figure 3-1 below shows the view of customer impact assumed by step loss functions and parabolic loss functions. State B represents the customer's specification for a particular characteristic of quality. Note that in the step function case, a plant would assume that any value of the quality characteristic up to A (in the negative direction) would be equally acceptable. The continuous function clearly shows that customers prefer B to A (in the sense that their "utility" loss is lower). Dirt rolled into the aluminum sheet at Rivertown provides an example of this issue. Most current inspection techniques and customer ratings are based on a step loss function. In real life, however, customers may begin to notice dirt before it gets to the reaction level, contributing to lower confidence in manufactured products.



Parabolic Loss Function

Step Loss Function

Figure 3-1. Parabolic vs. Step Loss Functions

Deming provides management with some views on organizational systems and performance metrics. In fact, he asks organizations to abolish management by objective. In Deming's view, firms should get rid of performance appraisal systems as they destroy teamwork and build up variability-producing functional walls. Daily production reporting and financial management systems should also be abolished at the plant level as these also drive myopic behaviors like building inventory buffers to hedge and playing numbers games near the end of reporting periods. [Scherkenbach, 1988]

In addition to eliminating traditional internal mechanisms, Deming suggests that employees should learn to deal with suppliers and customers differently than with current practices. His views on customers (partially described above) are simple: satisfy them now and in the long run. For suppliers, Deming asks that companies develop long term customer/supplier relationships that end the practice of awarding business on the basis of price alone.

The bottom line for Deming is that *quality* should be everyone's goal. Management does not exist to supervise, but rather to lead and educate all employees toward this goal.

3.1.2 Juran's Views -- Cost of Quality

Juran may be viewed by some as a bit more pragmatic than Deming, at least in the sense that American companies already have well-established methods and infrastructures for setting strategy and understanding the costs and benefits of doing business. Juran suggests that companies "...enlarge the strategic business plan to include quality goals. The processes for meeting these quality goals then parallel the processes long used for meeting traditional goals such as for sales, product development, and profit." [Juran, 1989] Juran believes that "...methods are available for quantifying costs of quality." [internal White Paper, 1992] These methods involve the identification of critical cost categories and linking them to actual plant behavior.

Juran does not say that the traditional Quality Department in U. S. companies has accomplished the quality goal of "fitness for use." [Juran, 1989] In that they housed experts in Quality Engineering and Reliability Engineering (Quality Assurance or QA), such departments provided benefits of reduced risk that defective products would be shipped to the customers. The problem is that such activities tend to foster the belief that only QA has to worry about quality. In addition, this structure hampers attempts to search for root causes for quality problems by creating human bottlenecks to information flow. [Juran, 1989]] Juran advocates the implementation of his Trilogy--Quality Planning, Quality Control, and Quality Improvement--to achieve customer satisfaction while optimizing profits.

Quality Planning involves first determining who the customers are and what they need. From here, firms need to develop product features that satisfy these needs and capable processes that can build these product features. Finally, Quality Planning requires companies to transfer quality plans to operating personnel. [Juran, 1989]

Quality Control involves evaluating quality performance, comparing actual performance to quality goals, and acting on the differences (essentially the DCA of the PDCA wheel.) Juran stresses that for Quality Control, managers, supervisors, and workers need measurements and relationships between process variables and product results. [Juran, 1989] Here, firms should search for and document root causes, create and use process models, and develop control and capability plans for each process.

Quality Improvement yields breakthroughs in process and product quality. Juran says companies should establish a quality infrastructure, identify improvement projects, set up project teams, and provide the resources to: diagnose causes, stimulate the establishment of a remedy, and establish controls to maintain the gains. [Juran, 1989]

Much of Juran's plan, including his call for maximum delegation, parallels Deming closely. The difference, it seems, is that Juran believes that inspection and quality cost reporting do play a role (at least in the foreseeable future) in the firm that is attempting to maximize profitability and quality.

Firms like NAC have traditional management and quality assurance structures, and these structures support the jobs and livelihoods of thousands of workers. This situation creates enormous inertia resisting the adoption of Deming's philosophies. Most of his philosophies, though, are in complete agreement with those of Juran. Things like PDCA cycles, process control and capability toward variability reduction, understanding customer needs, and increased worker power and responsibility must form the backbone of a successful quality program.

To the list in the preceding sentence, we will add Cost of Quality (COQ), attaching to this recommendation a hypothetical note of dissent from Deming. Because firms are unlikely to be able to change their processes, customer/supplier relationships, hierarchies, and individual workers' education, biases, and philosophies in the near term, it does not seem possible that they could become "Demian" overnight. Rather, this work, echoing Juran and others, proposes that established companies change the metrics they are reporting to those that will drive desired behavior. For quality goals, a Cost of Quality Framework can help the drive.

3.1.3 COQ Framework -- What Costs?

Before one begins to assign costs to quality, it may help to define what quality is. One such definition splits quality into various dimensions including product performance, features, reliability, conformance, durability, serviceability, aesthetics, and perceived value. [Andreou, 1991] Certainly, firms have recognized in recent years that quality includes more than just immediate customer satisfaction with the product characteristics.

Using a technique developed at Penn State called Relative Perceived Value Analysis [Gross, 1991], NAC has identified the following attributes which together determine the relative "Quality" of NAC products: physical product quality (surface appearance, consistency), performance (in making end products), delivery, services, expectations, terms, price, relationship, and supply base.

Built into the "physical product quality" category is surface quality (including coatings) and other elements leading to a perception that the product is consistently superior in appearance and function. The problem with a rigid definition of quality is that the marketplace has become extremely dynamic. Sources of change in the aluminum sheet market, for example, include downgauging (which can create more performance problems as well as highlighting surface defects that might not appear in thicker metal), increasing competition (NAC's competitors now have the ability to produce products that were previously the exclusive domain of NAC), and higher surface quality expectations (due in part to the increasing use by customers and other suppliers of automated inspection devices that can identify extremely small defects in the metal surface.)

Whether or not it is a moving target, defining the dimensions of customers' "Perceived Value" can certainly aid a firm in understanding the word quality. On the other end of the spectrum (if we are to use COQ to link quality to behavior) is understanding the in-plant drivers of quality. Grouping activities according to Porter's "Value Chain Analysis" [Andreou, 1991] provides one such classification.

Activity-Based Costing (ABC), implemented at many firms, may allow for easy identification of the activities in the value chain. ABC attempts to trace costs to products by allocating overhead costs to the most important activities involved in the production process. Such systems are based on the assumption that "Products consume activities and activities consume resources." [Andreou, 1991]

ABC requires the identification of cost drivers, a sub-set of which could be called "Quality Cost Drivers." These drivers are at a low enough level that we can understand what they cost and how they impact quality. They include product tolerances, process capabilities and limitations, product producability, manufacturing systems and procedures, human error and variability, breakdowns/machine failures, set-ups, tooling, schedule stability, and inspection. [Andreou, 1991]

The Quality Cost Drivers can be grouped using a variety of classification schemes. The one most prevalent in the literature subdivides quality costs into prevention, appraisal, and failure costs. Usually, one splits failure costs further into internal failures and external (at the customer) failures. Examples of each follow:

Prevention -- training, planning and execution of process improvement or redesign efforts, and promotion of quality goals

Appraisal -- inspection costs including people, supplies, and equipment, as well as costs for destructive testing (where some product is lost)

Internal Failure -- scrap costs, rework costs, work interruptions, and re-inspection costs

External Failure -- sales losses on returns, special allowances, warranty costs, and canceled future sales orders [Edmunds, 1989]

Most of the costs included above can be readily obtained, particularly for firms with a good ABC system. Only the external failure costs, in particular the cost of canceled future sales orders, may be difficult to assess.

For an initial implementation of COQ, Juran has revised previous claims that a full-blown system is the "right thing to do." His latest works suggest that the easiest, and perhaps most important, costs to report are just the Cost of Poor Quality (COPQ). [Juran, 1989] These costs are the sum of internal and external failure costs above. By tracking these, a company can estimate the magnitude of out-of-pocket expenses incurred due to poor quality. If a firm wishes to do cost/benefit analyses with COQ data, individual projects' appraisal and prevention costs may be evaluated separately.

3.1.4 Include the Customer

As the new view of the manufacturing organization may be more like that in Figure 3-2 than in the traditional organization, the typical separation of sales and production seems somewhat counter-productive.

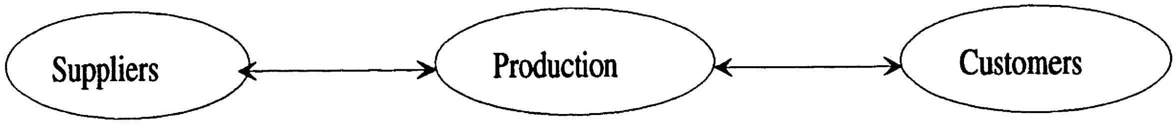


Figure 3-2. New View of Organization

In fact, this figure urges companies to think about the manufacturing plant as a dynamic system, characterized by a high degree of interdependency of processes, a central focus on the customer, and an understanding of and immediate attention to customer feedback.

With this frame of mind applied to the COQ framework described above, external failure costs should not be ignored. Yet, because portions of these costs are hard to estimate, many implementations of COQ tend to ignore this entire category of COQ. [Andreou, 1991] This may be the reason that Deming feels so strongly that COQ will lead to a perpetuation of the status quo.

Several approaches have been tried to value the impact on future purchasing decisions of current quality. Most have relied on the PIMS collection of marketing data to try to draw regression correlations between quality, market share, and profitability. Unfortunately, "...no clear relationship between price and quality [or market share] except where there are obvious differences in features and performance of the products under consideration..." [Andreou, 1991] has been found. This may be due to the inherent limitations of the PIMS database or to other biasing in the regressions.

It does seem reasonable, though, that improvements in quality can create strategic opportunities to reaffirm relationships with existing customers, acquire new customers, define new market segments, and create product differentiation that may lead to higher profit margins. One way to look at valuing these strategic opportunities is to think of high quality as an option purchased for upside market potential. [Andreou, 1991] If most firms in an industry move to a new level of quality, but one firm maintains the status quo, this firm will incur significant costs relating to the decision not to purchase the option.

All of these economic theories may sound nice, but companies are still faced with the problem of valuing the impact of quality on purchasing decisions. In the absence of specific useful longitudinal data with which to construct quality loss functions, companies may have to resort to the intuition of sales and marketing people to get order-of-magnitude estimates. Another approach, taken in this thesis, is to ignore these costs for the time being, while recognizing that the true cost of external failures will be undervalued. Firms that are interested in reducing the true cost of quality should begin keeping accurate data on actual sales versus customer satisfaction on all dimensions of quality. Even without an opportunity cost of lost sales estimate, however, external failure costs should be included as a category in any COQ analysis and may be supplemented by a non-financial metric such as customer incident rate.

3.1.5 Uses of COQ

With raw COQ data and such ratios as quality cost/sales, scrap costs/direct labor, warranty costs/sales, quality cost/asset value [Edmunds, 1989] companies may begin to work on improving quality and profitability. As NAC mentions in an internal White Paper, COQ can help a plant or company define opportunities for quality improvement (by linking a Pareto of costs to underlying root causes), select those projects with the highest Net Present Value (NPV), and monitor progress toward variability reduction. [NAC, 1992]

COQ can help companies begin to measure things which did not previously have metrics associated with them. Such activities include customer satisfaction programs, continuous or "Step Change" improvements, and benchmarking efforts.

Finally, with accurate data and a careful implementation of a COQ system, reducing COQ will lead to an increase in Return On Assets (ROA), currently a popular performance metric. ROA defined as income divided by total asset value goes up with increasing revenue from higher market share or better bottleneck utilization, with decreasing costs due to lower failure and appraisal costs, and, over the long term, with reductions in capital assets due to more efficient production processes.

3.1.5 COQ and JIT are not Contradictory

One argument against the implementation of Cost of Quality Systems is that a goal of reducing COQ may contradict efforts at the plant level to create Just-In-Time (JIT) production systems. In fact, traditional tradeoff analyses suggest that for both inventory reduction (one element of JIT) and quality, there exists an optimal, non-zero level (see Figure 3-3).

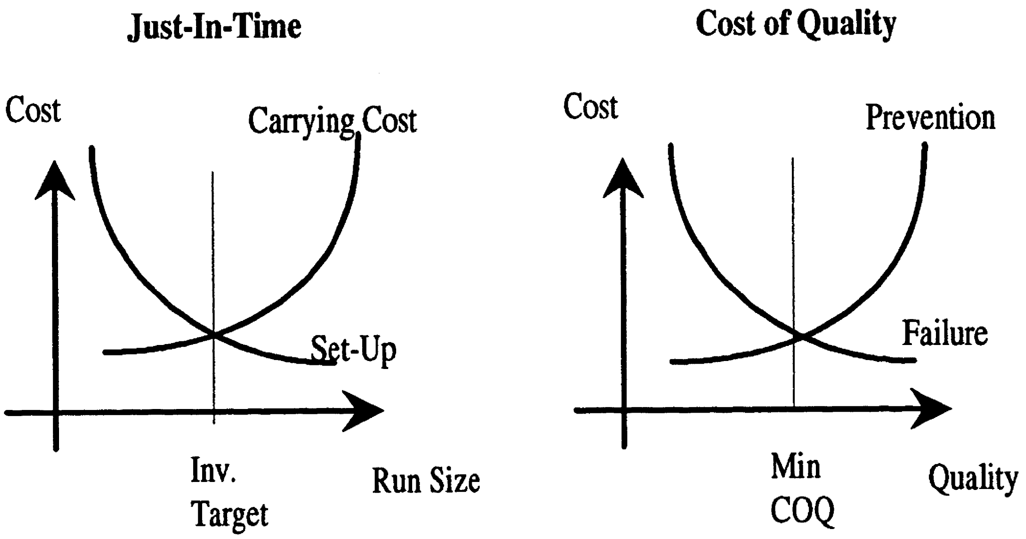


Figure 3-3. Just-In-Time and Cost of Quality Tradeoffs

But, "...JIT inventory systems and 'Total Quality Control' (TQC) approaches would seem to disregard the economic tradeoff nature of inventory and quality control decisions." [Mefford, 1989] They do this because they rely on substantial productivity effects to simultaneously reduce COQ and costs of zero inventory.

The productivity effects that will ultimately alter the functional form of the preceding graphs come from a variety of sources. For inventory, the better scheduling, reduced set-up time and cost, more efficient maintenance, and more flexible management that are required to make JIT work all add to productivity. [Mefford, 1989] In addition, more efficient shop-floor control tends to improve quality, while lowering work in progress (WIP) inventory leads to reduced losses due to damage during handling or storage. [Mefford, 1989]

The primary quality effect on productivity is more obvious because it is direct, since only good products appear in the numerator of the productivity equation. Indirect effects of higher quality include better product design, improved process efficiency, higher demand, and higher worker morale (particularly when we make the link between quality and performance). [Mefford, 1989] Adjusting the above quality figure for productivity, we can add an additional cost to the prevention/failure framework: *inefficiency*, which is the opportunity cost of poor productivity. It impacts the above quality curves by shifting them to the right. As Figure 3-4 shows, this results in a higher target level of quality to minimize costs. (This still suggests that zero defects may not be optimal, but at least the target value for quality should be higher than it is currently.) This type of analysis suggests that JIT and COQ programs may not be contradictory and less-than-optimal when plants go after the productivity increases that complement both. [Mefford, 1989]

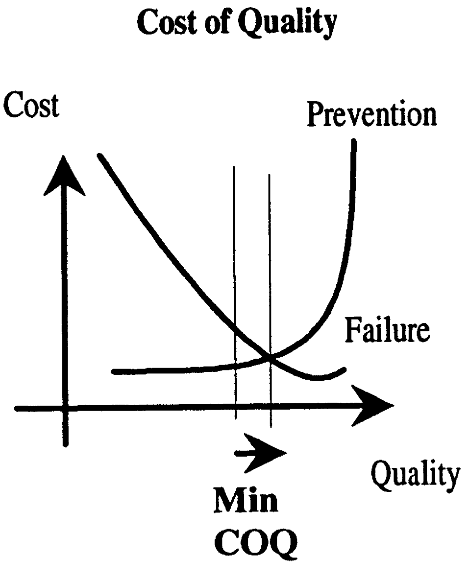


Figure 3-4 Productivity-Adjusted Cost of Quality

3.1.6 Organizational Aspects to Consider

The implementation of any of the above elements of Total Quality Management will require significant investment of employee time and some drastic organizational changes in most companies. Where quality was typically an after-thought, appended onto an existing process because the customer had started to demand improvement, it must become a way of life. Just as manufacturers that utilize environmentally hazardous chemicals in their processes have re-engineered their processes to both reduce emissions and improve profitability, so must companies rethink the way the organization implements quality.

Joiner Associates [Scholtes] provides a high-level approach for the "quality transformation" that focuses on:

1) Managers as exemplars, educators, and leaders of change

2) Process improvement projects utilizing TQC tools led by cross-functional teams

3) Top management support and planning for initial start-up and expansion

of quality programs

4) Attempts to change the organization's culture toward one more supportive of TQC

5) Education and training for all employees

In some sense, this sounds very much like many of the failed quality programs instituted during the early 80's. The difference this time should be item number 4 above: change the organization's culture.

If we believe the Fifth Discipline [Senge, 1990], the single most important role of leaders in an organization is to define and put in place a different structure or culture to affect real and lasting change. As soon as this culture truly supports quality activities and variability reduction, companies can begin to reap the benefits long promised from such activities.

3.1.7 COQ at Other Companies

Many U. S. companies have implemented COQ as part of their overall quality efforts. General Motors, Avon, Corning, General Dynamics, AT&T, IBM, and Motorola all have formal COQ systems. These systems vary from simple, out-of-pocket failure cost (COPQ) tracking to full-blown cost accounting systems, however, one element is common throughout: the goal is to reduce (and ultimately eliminate) COQ from the cost of producing goods. [Harrington, 1989]]

3.2 Optimal Design of Control Charts and Inspection Systems

COQ systems allow users to monitor progress in improving quality costs and to rank prospective improvement projects in terms of their costs and benefits. However, these systems are typically not at a level of detail to help managers structure their inspection system to minimize costs. To get to this level, quality tracking systems must also include the type of data normally used to construct process control charts. With this objective in mind, we survey some of the literature available on the economic design of control charts.

Echoing the COQ framework presented above, Montgomery points out that:

> The design of a control chart has economic consequences in that the costs of sampling and testing, the costs associated with investigating out-of-control signals and possibly correcting assignable causes, and the costs of allowing defective products to reach the consumer are all affected by the selection of the control chart parameters. [Montgomery, 1980]

The "control chart parameters" include process means, upper and lower control limits, sampling intervals, sample sizes, and probabilities of defect generation. The economic tradeoffs are typically between the total cost of sampling (including false alarms) versus the expected cost when failures occur but go through the process undetected. [Montgomery, 1980]

Montgomery discusses models for many different types of processes including:

> i) those for single or multiple assignable causes, where the process either stops or is allowed to continue while the search for an assignable cause is completed
>
> ii) various process failure mechanisms from exponential random variables to Poisson processes

Such economic designs have been proposed for xbar, R, p, and CuSum charts.

Lorenzen and Vance [Lorenzen, 1986] proposed a general method for determining economic design of control charts. This method is based on the average run length of a measured statistic assuming the process is in control during the run and out of control otherwise in some specified manner. The objective of this model is to minimize the expected cost per hour for the following cycle: [Lorenzen, 1986]

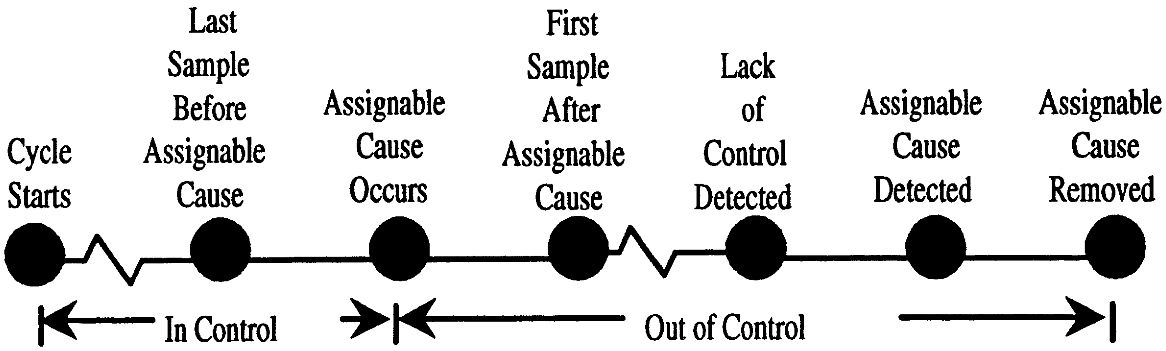


Figure 3-5. Lorenzen and Vance Control Cycle

Assuming that all defects are detected during an inspection and that defects do not get repaired (i.e. rolled over, becoming virtually invisible) later in the process, it may be possible to optimize the current inspection processes at each sequential step in a production process. A similar approach was utilized at Rivertown [Dodson, 1990] to optimize preventive maintenance schedules. The economically optimal solution to such problems is based on three assumptions:

1) preventive maintenance is performed on an item at time=t at a cost of C_p
2) if the item fails before time=t, a Failure cost of C_f is incurred
3) each time preventive maintenance is performed the item is returned to its initial state

With these assumptions, the average total cost of the item over some time period is simply equal to the cost of preventive maintenance plus the cost of failures:

$$C_{total} = P(X > t)C_p + P(X < t)C_f \tag{3-1}$$

where $P(X > t)$ = probability of no failure before time t

$P(X < t)$ = probability of failure before time t

Now, the average length of the time period shown in Figure 3-5 will be the probability weighted average of the time to fail plus time with no failures:

$$L_{total} = P(X > t)t + P(X < t)\frac{\int_0^t xf(x)dx}{P(X < t)} \tag{3-2}$$

where f(x) = probability density function for failures as a function of time

Note that $P(X < t) = \int_0^t f(x)dx$ (3-3)

Thus, substituting the above (3-3) into (3-1) and (3-2) and defining the steady state cost per unit of time (C) as $\frac{C_{total}}{L_{total}}$, we arrive at the following:

$$C = \frac{C_p\int_t^\infty f(x)dx + C_f\int_0^t f(x)dx}{t\int_t^\infty f(x)dx + \int_0^t xf(x)dx} \tag{3-4}$$

By substituting a particular probability density function for f(x) (Rivertown used a Weibull Distribution to model failure phenomena), one can write down a cost function to be optimized in terms of t.

The economic tradeoff implicit in the above derivation appears in all of the models used to optimize control chart economics. The important question to ask here is: Is it possible to create a reasonable objective function as in equation (3-4) above for an entire plant's inspection costs?

Even if we hold process variability constant, the number of different inspection techniques, the lack of metrics (often other than a p-chart type "It looks good" or "It doesn't look good) linked to the assignable causes of defects, inspection variability, and preventive maintenance schedules that may disturb underlying probabilities of defects, make it highly unlikely that large, complex plants will, in the near future, be able to create system-wide *explicit* inspection optimization. A goal of explicitly optimizing plantwide inspection as variability is reduced seems even less attainable.

Rather than search for this sort of complex model, the following methodology relies on an iterative approach to system-wide inspection "optimization" :

1) Optimize preventive maintenance and assignable cause-specific inspection on a machine by machine basis.

2) Assume that the results of such work produce a system characterized primarily by random events.

3) Model the combination of random defect generation and aggregate inspection in a simple fashion.

4) Link the model to cost data to allow Monte Carlo simulation of various inspection and variability reduction alternatives.

The analysis presented in Chapters 4 and 5 addresses items 3 and 4 of the above approach.

3.3 Utilizing Data for Process Understanding

The preceding section attempted to bridge the gap between ideal process control theory and practice, where even without a thorough understanding of defect root causes, we still want to produce quality product and attempt to make a profit. In this case, we will need to admit that some inspection is necessary and try to optimize its placement and specific design to minimize costs. At the same time, however, we cannot ignore the search for process understanding. This section provides a brief overview of some techniques that, combined with Statistical Process Control (SPC), can aid in physical understanding of production processes.

NAC realized that process engineers engaged in SPC are typically burdened by the processes of managing, analyzing, and displaying large quantities of data. Where they would rather spend their time searching for physical understanding, they probably waste too much of it simply handling data. [NAC Artificial Intelligence Group, 1987]

Computer tools have been developed and implemented that help with data management, statistical analyses, and graphical display of process control data. One such tool developed by the NAC Technology Center, helps to automatically detect and diagnose out-of-control situations in some real NAC processes. [Love, 1989] Using a nonlinear filtering scheme, the tool manipulates process input data to look for peaks (from amplitude thresholds), steps (from the integration of amplitude thresholds), and ramps (based on slope). Combinations of these basic events can be built into rulesets for diagnosis and reporting. [Love, 1989]

This sort of system frees engineers from having to analyze by hand massive amounts of control chart data. It ensures that significant events will be noticed. Finally, it facilitates the creation of a very useful process knowledge base that may lead ultimately to reduction in sources of variability.

Some drawbacks of these systems include long development times, large data storage requirements, complex connectivity, and a removal of some of the "by-hand" benefits of SPC. Taken with the benefits, though, some form of computer assistance is vital in achieving an understanding of plant processes in an efficient manner.

3.4 Long-term vs. Short-term Cost Analysis

As mentioned above, in order to use COPQ as an effective tool, one must consider which costs to include failure costs. Section 3.5 describes the *type* of costs that are included in each of the COQ categories in the Rivertown system. It goes on to make the argument (as does Juran) that a focus on failure costs, that is COPQ, is the right place to begin. To completely specify which costs to include, however, we must also consider the *time-frame* of the costs and of our management objectives.

Koetje outlined important work on the time-frame of accounting costs by other authors [S. Eldridge and B. Dale (1989), C. Fine and D. Bridge (1987), R. Mills (1988), J. Plunkett and B. Dale (1988), and T. Tyson (1990)] and used the following figure in an appendix to his Masters thesis [Koetje, 1991]:

		Use	
		Financial Reports *Long-Term Analysis*	*Short-Term Analysis*
Capacity	*Excess*	**Absorption**	**Variable**
	Shortfall	**Absorption + Opportunity**	**Variable + Opportunity**

Figure 3-6. Appropriate Costing Framework For Various Capacities and Planning Horizons

He defined absorption costing as standard costing using labor and overhead allocation based on pre-established "burden rates." Opportunity costing includes the opportunity costs of lost bottleneck resources under capacity shortfall conditions. Finally, variable costing is defined as purely variable, out-of-pocket expenses associated with particular events.

The above chart makes two important points. First, where a factory with a capacity shortfall encounters failures, we must value the opportunity cost of the lost business associated with that failure. Second, in the long-term, where capital and labor are not "fixed costs", we must consider the impact of failure on machine sizing and staffing requirements. In the short-run, or where capital expenditures have been arbitrarily limited, one should use only the actual incurred expenses (plus opportunity costs) to value failures.

If a plant uses a planning horizon of a few years, there is some danger that using only variable costs will underestimate the true aggregate costs of failure. Some suggest that the marginal failure only incurs out-of-pocket expense, but at what point do marginal failures, taken in aggregate, comprise an average failure rate that contributes to higher levels of capital and labor? Though cost/benefit analyses and return on investment calculations demand relatively exact cost figures, the truth is that we never have exact figures. Sources of error include allocation of fixed costs using standard "burden rates", variation in estimates of future cash flows, and data collection errors, which impact everything from cost estimates to engineering design parameters. The most important thing for capital budgeting for short-term process improvement is that we can *rank competing projects*. Provided that we have more positive Net Present Value (NPV) projects than money available for investment, we should not worry about assumptions built into the evaluation of all competing projects, particularly those that will not alter the components of the value-chain in the process.

The use of data like that produced by COQ systems requires one to remember the assumptions that went into its creation. Most firms that get into trouble with average metrics (the substance of most executive information systems), do so because they end up applying an average number to specific instances. Fortunately, in this thesis work, the labor force has been set at a constant level and capital expenditures limited to relatively low levels. Under these circumstances, variable costs, plus allocation of opportunity costs, can be correctly used to conservatively estimate overall costs. This cost basis will not be accurate enough, however, to justify individual significant capital investments in projects with a time frame of several years, or for projects where the underlying assumptions of this model are incorrect.

3.7 Chapter Summary

Chapter 3 should provide enough grounding in the theory behind COQ analysis to make Chapters 4 and 5 make sense. For a deeper look into quality theory, many works, including those referenced here, detail the views of Juran, Deming, David Crosby, and others. The mathematics of economic control chart and sampling plan design appear, from my literature search, to be less well understood from a system-wide perspective. The aggregate and occasionally qualitative approaches of quality specialists may help to bridge this mathematical gap between the accurate characterization of specific stochastic processes and the explicit characterization of systems with millions of components.

Chapter 4 -- Cost of Poor Surface Quality: Data and Model Development

4.1 Cost of Quality Components at Rivertown

Though this thesis focuses on the Costs of Poor Quality (failure costs), identification of some appraisal and prevention costs can help put the COQ framework into perspective. At Rivertown, general (surface and non-surface-related) appraisal costs include the following:

i) Quality Assurance Lab material and personnel costs (primarily for composition and physical property testing)

ii) Metal used for destructive testing (for surface defects this is primarily the 5-Stand test)

iii) Material costs for other tests (like chemicals and electricity for the continuous mill test)

iv) Processing time for large samples (if taken on the bottleneck)

Prevention costs typically include some ongoing as well as one-time project costs aimed at reducing process variability and the generation of defects. Some Rivertown examples include:

i) Enhanced process control on bottleneck polymer coating lines

ii) Ingot sawing to minimize surface defects due to microstructure imperfections near ends of ingots

iii) Mill cleaning to reduce dirt defects

iv) Increased mill maintenance (like roll changes) to reduce frequency of defects

As appraisal costs (mostly destructive testing) for surface defects comprise less than 10% of the COQ for surface quality, these costs can be ignored in a first cut look at the problem. Prevention costs can be evaluated on a case by case basis and, hence, do not need to be included in a COPQ framework. This leaves variable failure costs -- composed of the following elements -- as the primary component of COPSQ at Rivertown.

i) Processing costs wasted when metal is scrapped. Such costs include electricity to run mill motors and equipment (above costs like lighting and support usage which need to be used 24 hours a day), any variable overtime paid to workers as a result of marginal production, and raw material costs including metal, lubrication, solvents, and polymer (for coating.)

ii) Remelt costs, which will include some vaporization loss and will be higher for metal with polymer coating

iii) Opportunity costs of lost throughput

iv) Outsource costs (to avoid the full cost of iii))

v) Customer incident costs including transportation, sales representative overtime, rebates, and potential lost future business

vi) Inventory and handling costs of scrap

vii) Bottleneck safety stock required due to upstream scrap rates

viii) Impact on the bottleneck of smaller average lots. (If the bottleneck has non-zero setup times, then pre-bottleneck scrap may impact capacity of the bottleneck.)

Items vi), vii), and viii) are relatively small by comparison and were ignored in the analysis that follows. Customer issues [v)] are important and are included, but they are relatively consistent across products. The combination of processing, remelt, outsource, and opportunity costs (PROO costs), thus comprise the bulk of the complexity in developing a COPSQ analysis for Rivertown.

Variable PROO costs vary (on a per pound basis) depending upon:

1) Product type.

2) Location where scrap is taken.

Costs differ by product type for several reasons. First, the product type determines the processing path. This leads to the location-based cost differences described in the following sections. The processing costs on a given piece of equipment vary by product type due primarily to variations in composition (affecting formability) and width of the product. Note that scrap taken from the sides of a rolled sheet is much less expensive than that taken from the length of the sheet. This is because the cost of producing metal is directly proportional to the length of the coil to be processed (which is proportional to the machine time required) and less related to the width, (though some additional force is required to roll wider sheet.)

Figure 4-1 shows the possible places where scrap can be taken and where defects can be generated in a generic production system that has an identified bottleneck:

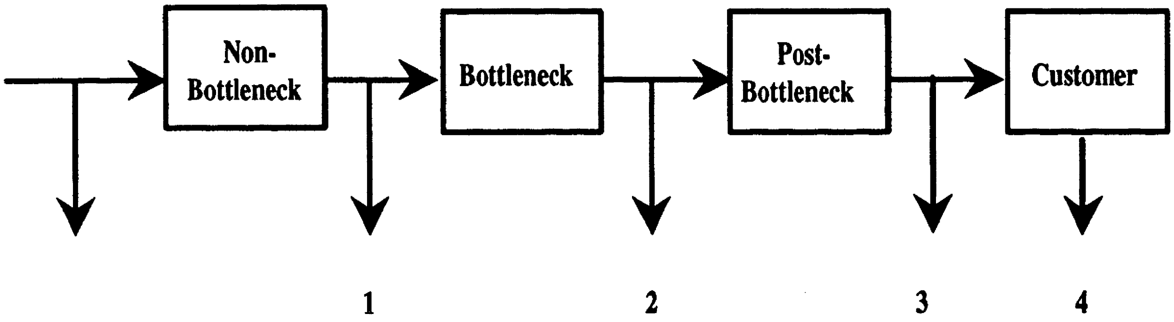
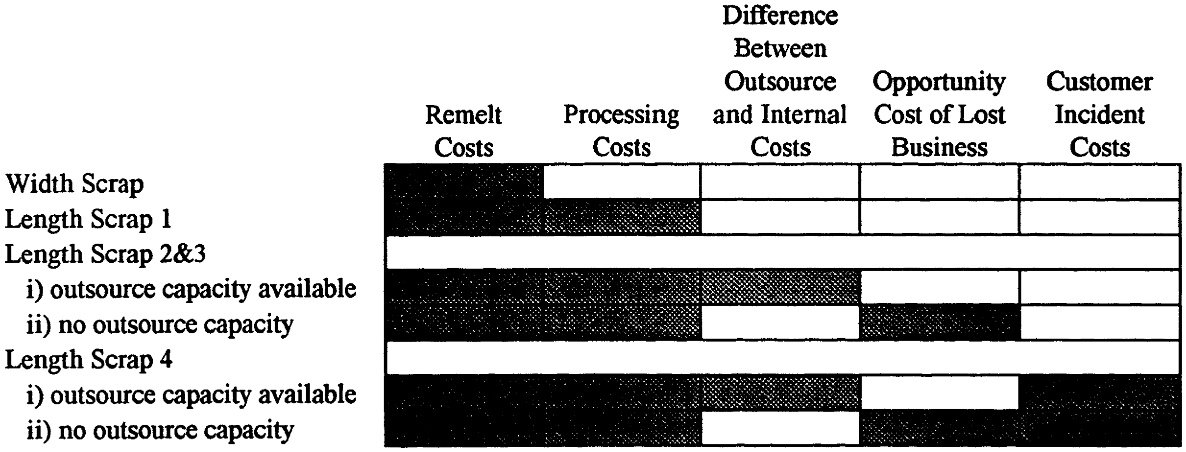


Figure 4-1. Potential Scrap Locations

There is an implicit opportunity cost related to scrap taken downstream of the point of defect generation. This cost is the difference in scrap costs between the point where the defect is identified and the point in the process where it is generated. The *Opportunity Cost of Missed Inspection* is included in the scrap costs described above, but should be recognized as something that can be reduced without altering the rate of defect generation.

In some cases, defects left in the system may actually have a negative opportunity cost of missed inspection. This can occur when we leave defective metal on the ends of a sheet to aid threading (which would result in scrap anyway) or to protect the salable inner "wraps" of a coil.

Figure 4-2 shows the components of the cost of scrap taken at an aluminum rolling facility with a process constraint as in Figure 4-1 above.



	Remelt Costs	Processing Costs	Difference Between Outsource and Internal Costs	Opportunity Cost of Lost Business	Customer Incident Costs
Width Scrap	▨				
Length Scrap 1	▨	▨			
Length Scrap 2&3					
i) outsource capacity available	▨	▨	▨		
ii) no outsource capacity	▨	▨		▨	
Length Scrap 4					
i) outsource capacity available	▨	▨	▨		▨
ii) no outsource capacity	▨	▨		▨	▨

Figure 4-2. Scrap Costs Depending on Location and Type of Scrap

4.2 Financial vs. Non-Financial Metrics

Chapter 3 introduced the concept of Cost of Poor Quality as a useful tool for identifying areas for improvement, ranking competing projects' benefits, and monitoring progress on quality issues. When implemented carefully, a reduction in COPQ will lead to higher profitability for a plant.

This is not necessarily the case for existing metrics at Rivertown. The metric recovery or yield serves as an example. Figure 4-3 shows COPQ and pound-based impacts of the top ten defects for a particular product:

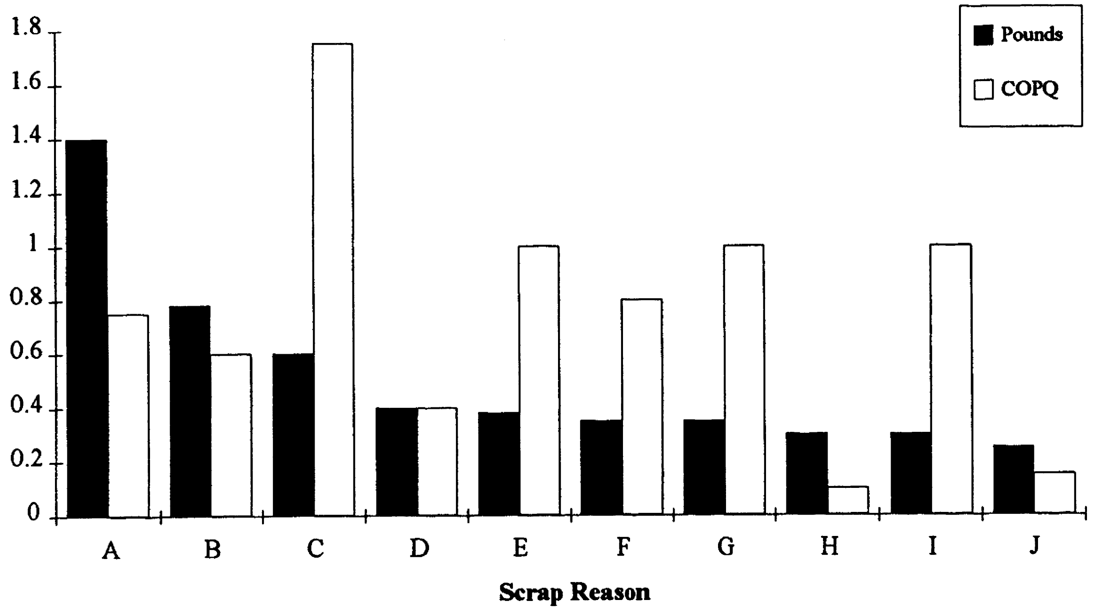


Figure 4-3. Internal Failure Costs For Product 1

Note that defects C, E, and G cost the plant the most, however, a ranking by pounds (which is independent of the location where the scrap was taken) puts the top three in order at A, B, C. If we were limited in funds for prevention projects, we might only undertake two projects. A ranking by pounds would completely miss defects E and G. This result would be clearly sub-optimal and should be avoided.

4.3 Breakdown of Cost of Poor Quality

The COPQ framework presented in Section 4.1 was used to calculate quality costs at Rivertown. Variable costs were estimated using an existing Industrial Engineering cost model that used product type and location as inputs. The model returned costs on a per pound basis by product type at each processing center. As there is a reasonable degree of width and gauge homogeneity within the Rivertown products, per pound variable costs by location and product should create a good first estimate of scrap costs.

By multiplying the number of pounds of metal scrapped at each location by the cost at that location for each product, we can estimate the total variable scrap cost.

Figure 4-4 shows the (disguised) value of these costs by type:

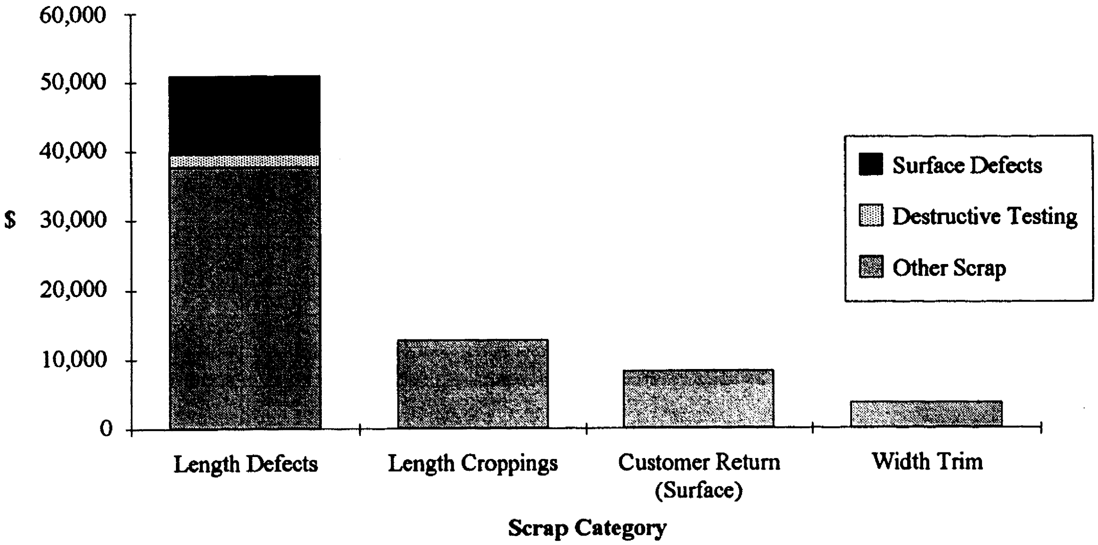


Figure 4-4. Rivertown Annual Scrap Costs

Here, destructive testing (actually an appraisal cost) is included to emphasize the relative magnitude of surface COPQ. Length scrap refers to scrap that reduces the length of a coil of aluminum for a metal or surface imperfection. Length croppings are typically metal taken during setup of a process or after the value-added work has finished. All width trim at Rivertown is in the form of planned trim to get the metal to final customer widths. Finally, customer return costs include actual out-of-pocket expenses for returns, but they do not include the impact of quality on future revenue.

Note that surface COPQ (internal plus customer returns) accounts for almost 30% of total scrap costs at Rivertown.

4.4 Surface Quality Defects

We may isolate a particular dimension of quality (as we have above with *Surface Quality*) if we can decouple its assignable causes from those of other dimensions. Fortunately for this work, the dimension surface quality can be treated as a separate problem because the root causes of such defects tend to be unique to this category. Thus, from this point on, this thesis will focus specifically on the Cost of Poor Surface Quality (COPSQ) and attempts to model it at Rivertown.

As defined earlier, surface defects are those that are visible on the outside of the sheet. Table 4-5 shows the top 11 (in terms of COPSQ) surface defects, their physical cause, and the Processing Center (PC) where the defect is generated. Note that these defects differ greatly in appearance between types and even within certain types (especially defects like rolled in dirt which may have very different sizes depending on the root cause of the defect.)

Defect Reason	*PC*	*Physical Cause*
Dents	Coater	more prevalent as down gauging occurs, related to handling, rollers throughout finishing processes, splicing techniques
Rolled in Dirt Type I	Hot Mill	short dirt streaks -- variety of sources: Hot Mill lubrication cleanliness, table rolls (which slab rolls on between reversing mill and continuous mill)
Coating Skips	Coater	non-flat metal, coating roller speed, coating viscosity, percent solids in coating
Pitted Roll Mark	Cold Mill	indentation (blemish) on roll from metal chips that causes a mark to be places on the sheet as it is processed
Butt Marks	Ingot Plant	startup transition for one of the ingot casting processes, relates to process control during casting (particularly for hard alloys)
Roll Mark	Cold Mill	disfigured work roll that cuts sheet at repeating intervals

Defect Reason	*PC*	*Physical Cause*
Slivers	Ingot Plant	magnesium inclusions formed in ingot casting (may also be other inclusion bodies that impact metal surface)
Waxer	Coater	control of application of lubricant at exit end of coating lines (must handle variable speed at beginning and end of coil)
Rolled In Dirt Type II	Hot Mill	long dirt lines -- variety of causes, but usually related to a gross contaminant (falling ceiling dirt, dirt on top of ingot)
Tray Dents	Coater	from handling of trays between Cold Mill and Finishing
Solution Stain	Cold Mill	lubricant drip (from pan or rolls) on coil after the last stand -- ends up on both sides of sheet

Table 4-5. Top 11 Surface Defects and Physical Root Causes

Notice that surface defects are generated by all process steps throughout the plant. As shown in Figure 4-3, the above cost ranking may not be exactly the same as the ranking by pounds due to variation in product type and defect location.

4.5 COPSQ Model Goal

To summarize, the goal of this particular analysis and modeling effort is to combine the underlying capabilities of the plantwide inspection system with the frequency of defect generation to help understand the components of Rivertown's COPSQ. Thus, we should understand everything that goes into the numbers reported in Section 4.3 so that we can model the important factors, monitor system performance, and carry out sensitivity analyses with respect to changes in inspection capability, defect generation, and inspection location.

4.6 Important Questions for Model Creation

The developer of any process model must deal with a complex set of tradeoffs and specifications. Based on the potential uses of the model, its anticipated in-service time, lead time for development, and available resources, a variety of options exist regarding the scope, complexity, and accuracy of process models. Other issues such as the definition of surface quality and cost numbers have already been addressed in this work. This section presents some of the important questions asked during the development of the COPSQ models employed in this thesis. Section 4.7.1 answers the questions from Section 4.6 as they would be answered for a relatively complex simulation model and Section 4.7.2 shows a flowchart of such a model. Section 4.8 answers the questions in the context of the expected value model developed in this thesis. Another possible simulation approach to this problem is discussed in Chapter 5.

1) What process pathway should be modeled and at what level of detail?

2) What are the appropriate "entities" for this model? (In other words, what unit should we say is "flowing" through these process pathways?)

3) How should we mathematically characterize the generation of defects?

    a) Can we link particular defects to particular process steps?

    b) Do we have mathematical models of such links?

    c) Are the occurrences of defects correlated across defect types? That is, if one defect has occurred is it more likely that another type of defect will occur?

    d) Are defects product specific?

    e) Do defects repair themselves downstream of the point of generation?

    f) How are the generation rates distributed? Two extreme possibilities are failure modes, where once a defect occurs, it continues until the underlying machine failure has been fixed, and random defects where occurrences of defects are completely unrelated.

g) Can lots have multiple defects (and of different types)?

h) Are defects more likely to be in certain areas of a lot? (More at the beginning/end, left/right, or top/bottom of the sheet.)

i) Is the amount of metal scrapped for an incident different based on defect type?

4) How should we mathematically characterize the capability of the tests at the different inspection locations?

a) Do we have mathematical models of the tests that would allow us to predict the impact of sample size or frequency changes on overall capability?

b) Are the tests performed consistently?

c) Are test capabilities related to the most recent defects (that have caused the most pain) or to each other?

d) Do we scrap metal that is actually acceptable to the customer?

e) Does the customer process metal that is defective?

f) If multiple defects are present, does the inspection tend to identify certain defects before it identifies others?

The answers to most of the questions can be represented by probability density functions, which in principle, could be used to develop a stochastic simulation model of the plant-wide inspection system and produce output functions showing COPSQ vs. time.

4.7 Complex Simulation Model

Although time and the availability of accurate data did not permit the COPSQ model developed here to utilize detailed answers to each of the above questions, such answers provide an important look at the structure of this problem and may guide future work on this subject. This section presents a conceptual model of the Cold Mill inspection process based on some observations made at Rivertown.

4.7.1 Conceptual Model Using the Cold Mill Example

This section answers the questions posed in Section 4.6 and describes the data needed to simulate the resulting system.

1) The level of process detail to be modeled is shown in Figure 2-1. Let us assume that we are concerned about only the highest value added product in the plant. Since this product just happens to all flow through only one of the three cold mills, we can use data for just one machine in the "Cold Mill" box in the flowchart. We will examine only Cold Mill defects and assume that they are either identified here or at a downstream customer.

2) The appropriate entity is a coil, since this is the physical lot that flows through the process and is examined at the inspection site shown. We will assume that defects either occur or don't and that they have some size distribution.

3a) Based on the exceptional ability of shop floor personnel to identify the source location of defects, we assume that we know which defects are Cold Mill related.

3b) Explicit models of defect generation do not exist.

3c) Based again on shop floor knowledge, we assume that defects are not correlated to each other.

3d) Because only one product type actually flows through the Cold Mill chosen here, we can ignore product dependencies on defect generation.

3e) We assume that Cold Mill defects will not repair themselves since no further reduction of gauge (which would significantly alter the microstructure of the metal) occurs after Cold Mill processing.

3f) There are two types of defects characterized by unique probability density functions for Coils Between Defects (CBD). CBD is defined as the number of good coils processed between defective coils. Estimates of the underlying distributions for these defects can be calculated from empirical data as follows:

i) Select a sample of CBD data points of size n.

ii) Choose an interval to group points into for a discrete probability density function.

iii) Calculate the frequencies f_i by counting the number of data points that fall into each interval i.

iii) Plot the height h(i) of each interval (note that intervals may be of different sizes) where:

$$h(i) = \frac{f_i/n}{c_i - c_{i-1}}, \quad c_i = \text{endpoint of interval } i \qquad (4\text{-}1)$$

[Hogg, 1987]

The results of the above calculations for two different defects are shown in Figure 4-6 and 4-7.

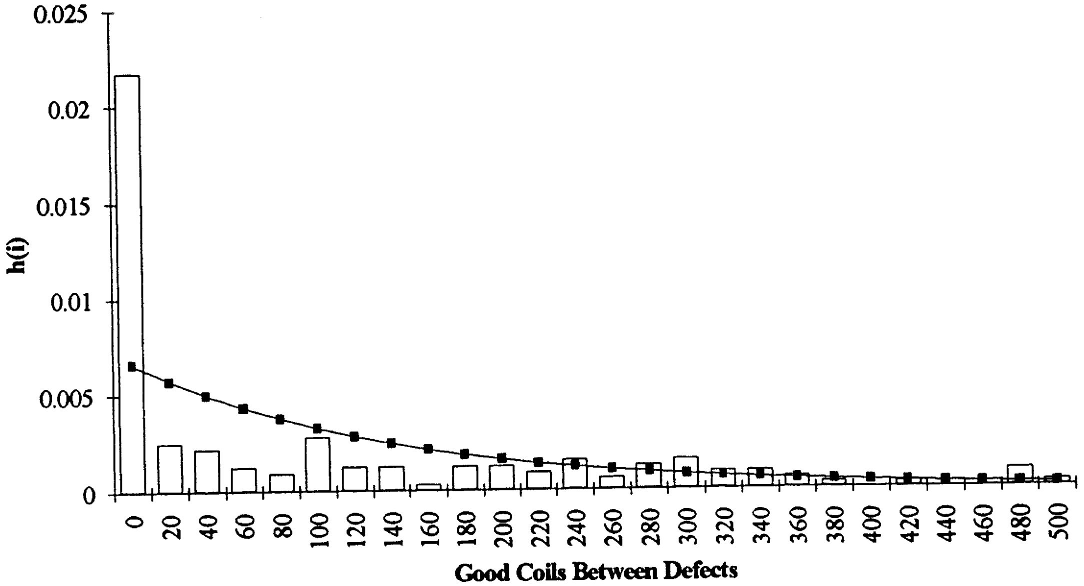


Figure 4-6. Relative Frequency Distribution for Defect A

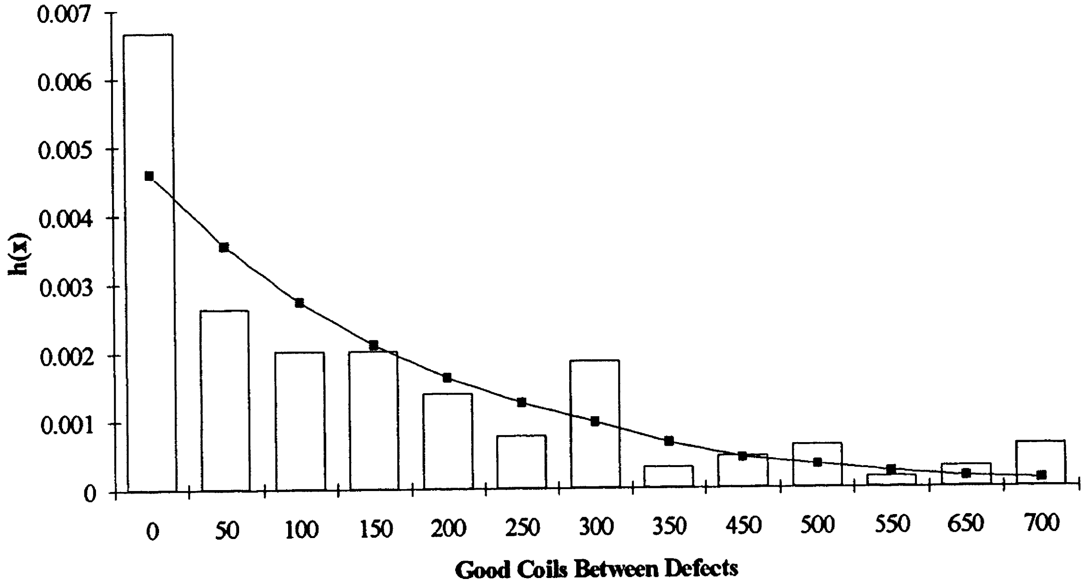


Figure 4-7. Relative Frequency Distribution for Defect B

Note that for Defect A, the distribution does not come close to matching that expected for an exponential distribution (the solid line.) For Defect B, one cannot reject the null hypothesis that the distribution is exponential at a 5% significance level using a Chi Square test [Hogg, 1987]. If we examine Defect A further, we find that, upon removal of the data for CBD equal to 0 through 9, we cannot reject the null hypothesis that the new distribution is exponential at a 5% significance level (see Figure 4-8).

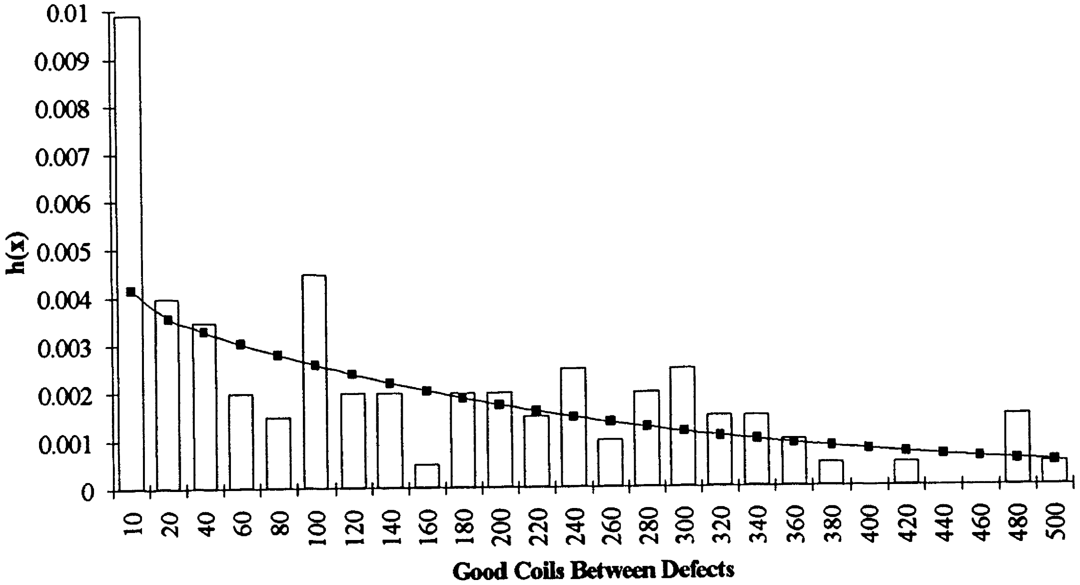


Figure 4-8. Relative Frequency Distribution for Defect A (Data from 0-9 CBD Removed)

Removing the low end elements of the histogram gives us one way to estimate Coils Between Events (CBE), where we assume that some failure occurs and continues to generate defects until it is fixed. As shown above, this distribution cannot be distinguished from a random one by a Chi Square test at 5% significance. Thus, we may group all Cold Mill defects into one of two categories. The first includes those defects characterized by random CBD. The other group has random CBE, with defects continuing to be generated until the underlying machine failure is identified and corrected.

3g) Coils can have multiple defects.

3h) We make the approximation that defects are randomly distributed across the sheet. Operator intuition suggests that this is an acceptable approximation for an "order of magnitude" model, but may require additional consideration to make the model more accurate.

3i) We look for a probability density function for the variable fraction of start weight scrapped per occurrence of a particular defect type.

4a) We assume that the ability of the human eye (the sensor for Cold Mill inspection) to identify defects varies by defect type and size. Thus, we look for a cumulative probability distribution showing the probability of identifying a defect up to a particular size (see Figure 4-9 for an example).

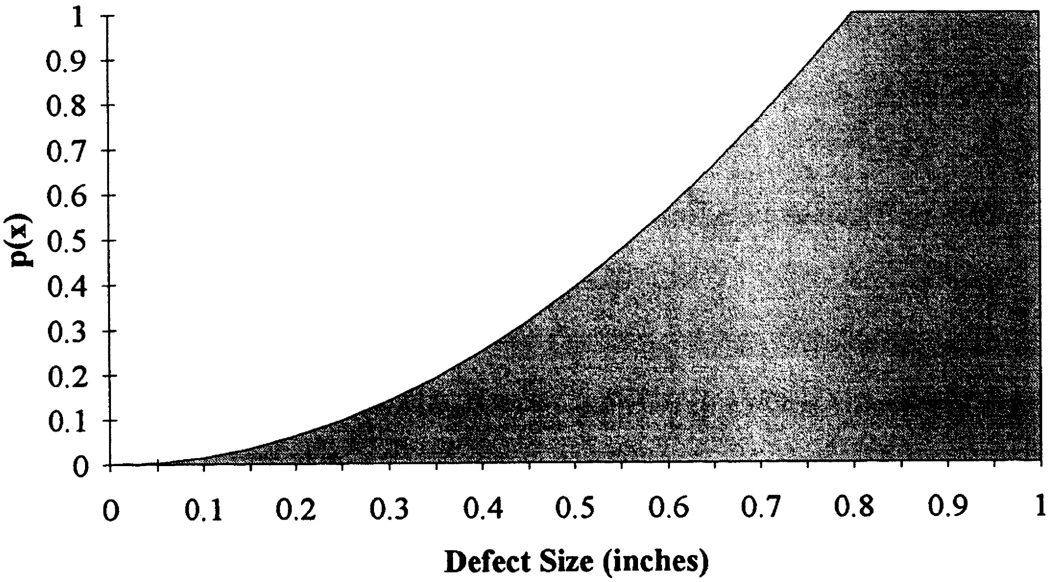


Figure 4-9. Cumulative Distribution for Test Capability vs. Defect Size

Sampling this distribution will give the probability that we see a defect of size x, p(x). If we have a constant sample size m_1, a coil (lot) length of L, and defects are randomly distributed across a coil, then we can calculate the probability that a given defect is seen:

$$S(x) = p(x)\frac{m_1}{L}. \tag{4-2}$$

Note that for some repeating defects, like roll marks, we should be able to calculate a sample size that ensures that we have the opportunity to see at least one of the defects on a defective coil (this will be discussed at greater length in Section 5.1.3.) For these defects, $\frac{m_1}{L}$ equals 1.0 and S(x) just equals p(x).

4b) For a given defect size with the same inspector, we assume that the tests are consistent. We may consider situations where different inspectors have different capabilities (however, these are not considered here.)

4c) We may hypothesize that inspection tends to be more capable in the days just after a major "event" when management devotes considerable attention to the cause of the problem. This non-linearity can be modeled by using different p(x) based on the time since last defect. In the absence of data to prove this, however, we assume that a single distribution for p(x) will be sufficient.

4d) There is a small, but finite, probability that a good coil is scrapped.

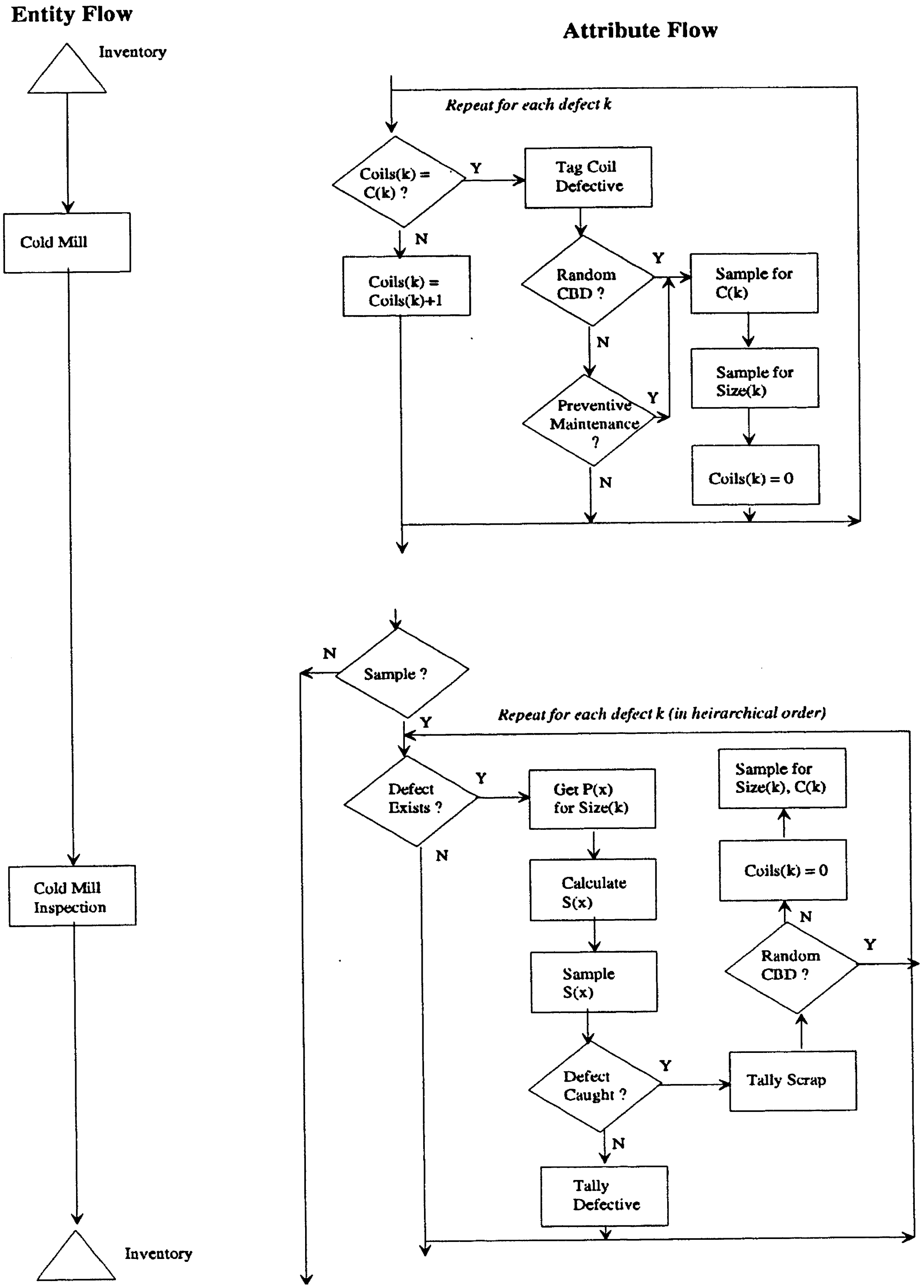
4e) Customers have their own p(x) which is not 100%.

4f) A "hierarchy" of defect-identifying ability does exist and can be included in the model by the order in which tests are applied.

4.7.2 Flowchart of Cold Mill Example Simulation

The flowchart shown in Figure 4-10 shows one way to look at the Cold Mill inspection process through simulation. *Entities* refer to the physical units that flow through the process; in this example, these are coils. *Attributes* are pieces of information associated with an entity and may change throughout the process. The key attributes here are whether or not the coil has a defect of type k and whether or not the defect is identified. This is only one example of the type of modeling that could be done on this system. Note that we might also add an algorithmic step to remove coils if the defective pounds per coil are over some threshold and for defects that may become repaired by further processing.

The key thing to note about the Attribute Flow is that we can build in very specific distributions for defect size, test capabilities, and CBD. Such a simulation will allow us to tally total pounds (if we add a distribution for pounds scrapped per occurrence) and coils defective, total scrapped, as well as cost totals for these quantities over time. We can then produce estimates of expected values for these totals as well as variance.



Entity Flow

Attribute Flow

Figure 4-10. Flow Diagram for Example Simulation I

4.8 Expected Value Model Assumptions and Limitations

The flowsheet provided above illustrates the usefulness of simulation models for COPSQ analysis and inspection understanding. Note that we can obtain output that allows us to view the variability as well as expected value of the COPSQ. We can alter the input distributions for CBE, CBD, defect size, and test capability. We can model changes in inspection frequency by altering m_1. By linking several modules like the one described above, we may even model the flow of defects through an entire plant.

The approach presented in Figure 4-10 was not used for the actual model developed during my time on-site, however, for several reasons.

1) Other complex simulation models developed for a variety of purposes had fallen rapidly out of favor as resources were unavailable for model upkeep.

2) Plant management was measuring quality to the customer completely separately from internal quality and had not yet embraced the usefulness of COPQ over traditional yield measures. This suggested that a simpler model might introduce management to the ideas contained in this thesis and encourage them to make the model more accurate and robust as they came to understand its usefulness and inherent limitations. I decided that an order of magnitude estimate that could be easily understood and might identify inadequacies in the data streams would be preferable to a complex system that might be impossible to maintain and interpret (regardless of its short-term accuracy.)

3) Much of the data discussed in Section 4.7 was unavailable or relatively inaccurate.

All of this led to some different answers to the questions in Section 4.6 as well as a decision to model only the expected value of COPSQ. (The new answers to Section 4.6 questions are shown below.) As discussed in Chapter 3, as long as we focus on the underlying root causes of defects, then undertaking projects that reduce COPSQ will lead to an improvement in quality and higher profits.

The approach followed in this thesis incorporated a specific set of assumptions, approximations, and model limitations that are enumerated below. This model is not a simulation model, but rather a reasonably simple spreadsheet model that gives the expected value of COPSQ based on some of the underlying probabilities of the surface inspection system.

The following answers refer to the questions listed in Section 4.6.

1) Process flow paths for specific coated products and a single D&I product were modeled. Due to similarity in product and machinery prior to Finishing process centers, Cold Mill data was rolled together as if a single machine did the processing.

2) Coils were chosen as the entity as in Section 4.7, however, data were not available for defect size distribution, so defect size was not included as model input.

3a) Based on discussions with plant Quality Assurance people, we can link defects to the PC that generated them.

3b) Explicit models of defect generation do not exist, hence we treat defect generation probabilities rather than the underlying process parameters that yield those generation probabilities as input to the model.

3c) Based again on shop floor knowledge, we assume that defects are not correlated to each other across products or time. (Note that for an expected value model, this assumption is not needed.)

3d) We consider product dependencies in the flowpath in Finishing and by defining products that go through only one Cold Mill. All products flow through a single hot mill.

3e) We assume that no defects are repaired by downstream processing. This is not an accurate assumption, however, data was not available to estimate its impact. Qualitative observations by shop-floor personnel suggest that the number of occurrences of this phenomena is small.

3f) This model treats all defects as characterized by a random CBD distribution (as calculated in Section 4.7.) Chi Square tests for most of the defects at Rivertown reveal this to be a reasonable assumption. For some repeating defects like roll marks and lube stains, it is not accurate over short time periods. However, as this model only produces an expected value of COPSQ and was intended to do so over a time period of about one year, the results will satisfy our "order of magnitude" criterion.

Figure 4-11 shows an example of the type of errors one might find with the expected value model. This simulation predicted the number of defective coils at the Cold Mill for one defect type. Note that the expected value model does a reasonable job of predicting the number of defective coils over time, however, there are some periods (from 120 to 210 for example) where the model will be off by up to 10%. This points out the sensitivity of any model to the data used to calculate the inputs. In this case, we may expect some error due to variation in the input data.

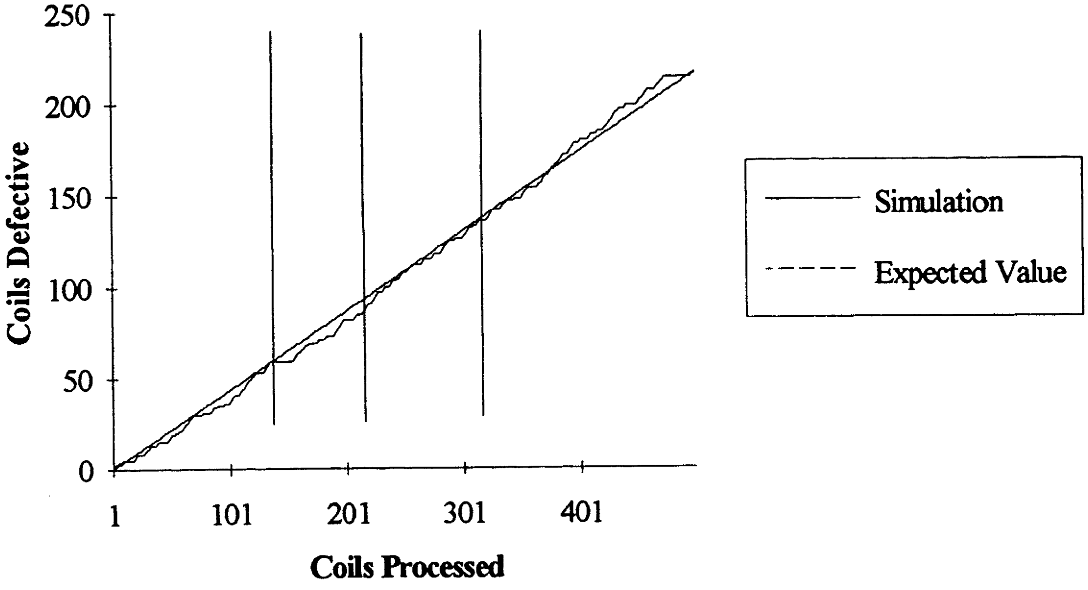


Figure 4-11. Comparison of Number of Coils Defective -- Simulation vs. Expected Value

3g) Coils can have multiple defects. The underlying data from which the probabilities used in the model were calculated does not allow for this to occur in cases where an entire coil was scrapped. This introduces an error that should be small considering the relatively low frequencies of generation of defects that result in whole-coil scrap.

3h) We make the approximation that defects are randomly distributed across the sheet in a two-dimensional spatial Poisson distribution, based again on shop-floor intuition.

3i) We use the expected value of fraction of coil scrapped by defect.

4a) We assume that test capability is constant over time for a particular defect at a particular test site. Again, this might lead to errors in the simulation case, but for an expected value model, it will not bias our estimate of COPSQ.

4b) Again, we do not consider the impact of different inspectors or of defect size.

4c) Our assumption of constant test capability does not allow for changes in capability over time.

4d) We assume that there is no probability that a good coil is scrapped. This undoubtedly introduces some error, but only because some customers may be more lenient than others. In the long run, it is probably good for the plant to assume that if an operator sees a defect, the customer will also.

4e) In the absence of hard data to the contrary, we assume that customers identify all defects sent to them. This is definitely not the case, however, one may make the argument that what the customer does not see will not hurt them. The problem with this assumption is that over time, standards as to what constitutes a defect may change. This may be the single largest source of error in this model and should be verified or improved upon in future research.

4f) Because the model here predicts expected value and is not a discrete simulation, there is no need for hierarchies. Note that the assumption in 3g) that the number of occurrences of multiple defects is small helps to support this position.

Again, though many of these assumptions are indeed significant, the purpose of this model is to help management deal with plantwide inspection planning over periods of one year or longer. In this case, we assume that the historical average values of the underlying parameters (adjusted, of course, based on all available knowledge) will provide reasonable estimates of those parameters over the course of a year.

4.9 Model Inputs

Based upon the assumptions, approximations, and limitations described above, we can model the expected value of COPSQ at Rivertown using a spreadsheet. The inputs to this model: test capabilities, defect generation rates, cost data, and average pounds per incident were calculated with data from the Production Tracking System (PTS) at Rivertown. The inputs to this system include information captured from Mod Comp process control computers, inline control, tracking, and monitoring devices (like scales), and human-entered input. The data must be accessed through data manipulation packages on either the Sperry system or the DEC VAX which has FOCUS software.

An additional source of data provides scrap and shipment information for Rivertown's external customers. Each time a customer returns metal, a Damaged Material Report (DMR) is completed and entered into the Customer Return System (CRS). The scrap codes in this system are different from the ones in the PTS system, but the underlying root causes are linked. The CRS data has been loaded into the FOCUS database and a cross-reference of scrap codes has been created with the help of the quality experts plantwide. Creating the cross-reference aided some MIS work-in-progress but also served to emphasize to plant management the importance of treating the customer as the last step in the production process.

The specific data fields that were available include (for every coil processed through the system): process date, process time, processing weight (actual or calculated -

- there will be some error in this), scrap reason, scrap weight, process PC, scrap PC, and scrap charged PC (PC to which the underlying root cause is assigned). Six months of historical data were available.

4.9.1 Model Input -- Test Capability

For the model, we treat the test opportunities (according to the planned frequency) as Bernoulli trials where plant personnel either identified or missed a particular defect on a coil (for a particular product type). We define:

Q_{ij} = the conditional probability of identifying defect i at PC $_j$ given that the coil has defect i at PC $_j$. (4-3)

The subscript j goes from 1 to N where N is the last sequential step in the production process. The subscript i goes from 1 to M where M is the total number of defects identified. There is a unique stage j(i) that identifies the particular PC that generates defect i. We can obtain an estimate of Qij from:

number of defects i identified at j / number of defects i identified at all PCs at or downstream of j

Figure 4-9 shows an example of the test capability calculation for a flow path with 4 processing centers:

j	Number of Coils Scrapped at PC j	Number of Coils Scrapped at or downstream of j	Test Capability
1	2	10	20%
2	3	8	38%
3	4	5	80%
4	1	1	100%

Figure 4-12. Example Test Capability Calculation

Figure 4-13 shows an example of the spreadsheet representing test capability for a particular product (note that Figure 4-14 shows where these defects are generated):

	Defect A	Defect B	Defect C	Defect D	Defect E	Defect F
Hot Mill	1	0.33333	0.75	0	0	0
Cold Mill		0	0	1	0.75	0
Coater		0	0		0	1
Customer		1	1		1	

Figure 4-13. Test Capability by Processing Center for Various Defects

The column on the left represents the process path for this particular product (it is a coated product). The row headings represent particular defects. Each element in the matrix represents the probability that a coil with that particular defect is identified at the PC to the left. Note that somewhere in each column there is a 1 corresponding to 100% inspection capability. If this does not occur before the customer, then, based on assumption 4e) from Section 4.8 above, a 1 is placed in the customer position. If one views the columns as the flow of defects through the process, no defects get past a process step with a 1 in it.

4.9.2 Model Inputs -- Defect Generation Rates

Defect generation rates are calculated using the same scrap data used to calculate test capability. We define:

$P_i =$ the probability that a coil passing through PC $_j$ gets defect i. (4-4)

We obtain an estimate of P_i from:

total coils with defect i/total coils

for each product/defect combination.

Figure 4-14 shows these values for the same product as in Section 4.9.1:

	Defect A	Defect B	Defect C	Defect D	Defect E	Defect F
Hot Mill	0.00063	0.0019	0.25	0	0	0
Cold Mill	0	0	0	0.00259	0.00345	0
Coater	0	0	0	0	0	0.02492
Customer	0	0	0	0	0	0

Figure 4-14. Defect Generation Rates by Processing Center for Various Defects

Remember that these values represent an estimate of the probability that *a coil* has a defect and may bear little resemblance to a process yield measurement based on pounds. Note that defects as defined here are unique to a PC, thus only one element in a given column will have a non zero entry.

4.9.3 Model Inputs -- Costs

Variable costs were calculated using the framework described in Chapter 3. An industrial engineering department model produced the following costs (the actual values are disguised):

Product	PC where identified	Setup Value	In-Process Value	Scrap Remelt	Opportunity Costs
End Stock	Ingot	0.08	0.09	0.051	0
	Hot Mill	0.10	0.155	0.051	0
	Cold Mill	0.16	0.165	0.051	0
	Coater	0.17	1.10	0.09	1.50
	Customer	1.10	1.20	0.09	1.50
D & I	Ingot	0.08	0.09	0.051	0
	Hot Mill	0.10	0.155	0.051	0
	Cold Mill	0.16	0.165	0.051	0
	Slitter	0.17	0.70	0.09	1.25
	Customer	0.70	1.00	0.09	1.25

Figure 4-15. Scrap Cost Table ($/pound)

Note that cost depends on i) product type, ii) location where defect is identified, and iii) plant capacity constraints over the model run. Based on the logic presented in Section 3.4, one can calculate the scrap cost by adding up appropriate elements of the above matrix.

Opportunity and scrap remelt costs were discussed in previous sections. The difference between Setup Value and In-Process Value recognizes that some defects are scrapped before consuming process time (setup) while others are scrapped on-line or after processing, having consumed marginal production resources (or worse, reducing plant capacity if scrap occurs on a bottleneck production center.)

4.9.4 Model Inputs -- Fraction of a Defective Coil Scrapped

As mentioned in Section 4.9.2, the defect generation rate utilized by this COPSQ model gives the probability that a coil has a defect. We also want to know the fraction of start weight scrapped per defective coil. Though in reality this quantity is best represented by a distribution of values, here we assume that it is a fixed proportion. Hence, we define:

A_i = fraction of start weight scrapped per defective coil for defect i. (4-5)

The data for the product shown above is displayed in Figure 4-16.

Defect A	**Defect B**	**Defect C**	**Defect D**	**Defect E**	**Defect F**
0.157	0.594	0.5	0.12	0.011	0.099

Figure 4-16. Fraction of a Defective Coil Scrapped for Various Defects

4.10 Model Mathematics

The preceding inputs may be combined to give the expected value of the following (for a particular product): the number and cost of defective pounds scrapped, and the number and cost of defective pounds that go through a PC onto the next step in the process. We will examine first a simple example where there is only one defect and two process steps. From there, we will expand the model to create formulas allowing us to calculate COPSQ as well as the Opportunity Cost of Missed Inspection (OCMI) for an entire product across all defects.

4.10.1 Single Defect, Two Process Steps

In this case, the matrix for each of the above inputs simplifies to a 2x1 column vector. Assuming that our two processing steps are Hot Mill and Customer, and we are examining Defect C, we have:

$i = 1$ representing "Defect C" above

j = 1 through 2, where 1 corresponds to the Hot Mill and 2 corresponds to the Customer

P_1 = probability of generating defect C = 0.25
Q_{11} = conditional probability that defect C is identified at the Hot Mill = 0.75
Q_{12} = conditional probability that defect C is identified at the Customer = 1.0
A_1 = fraction of pounds scrapped for a coil with defect C = 0.50

Start with a throughput (T) of 100,000 pounds and calculate the expected value of the total pounds scrapped and the total pounds defective (and sent to the customer):

This calculation is based on Bayes Theorem [Hogg, 1987] which states that:

$$\text{Prob}(XY) = \text{Prob}(Y) * \text{Prob}(X|Y), \text{ for two events X and Y} \tag{4-6}$$

In terms of the variables presented in the previous sections:

$$\text{Prob(coil is defective and scrapped at the Hot Mill)} = P_1 * Q_{11} \tag{4-7}$$

$$\text{Prob(coil is defective and not scrapped at the Hot Mill)} = P_1 * (1-Q_{11}) \tag{4-8}$$

We can convert these to pounds using the fraction scrapped for defective coils (A_1). Thus, we can the expected value of pounds scrapped at the Hot Mill:

$$\begin{aligned} \text{E(pounds scrapped at Hot Mill)} &= Q_{11} * P_1 * A_1 * T \\ &= (0.75)(0.25)(0.50)(100{,}000) = 9{,}375 \end{aligned} \tag{4-9}$$

Note that dimensionally, this yields:

(coils/coils)*(coils/coils)*(pounds/pounds)*pounds = pounds

E(defective pounds sent to the Customer) = $(1-Q_{11}) * P_1 * A_1 * T$ (4-10)

$= (.25)(.25)(.5)(100{,}000) = 3{,}125$

Hence, our traditional yield measurement would give a recovery of:

(100,000 pounds started - 9,375 pounds scrapped)/100,000 pounds started = 90%

Note that this measurement does not count the 3,125 pounds that got to the customer, nor does it take the cost of scrap into account. Adding costs to this analysis requires some simple modification of the formulas and the recognition that scrap taken at the customer does cost money. In this case, with scrap costs D_1 = cost of scrap at the Hot Mill and D_2 = cost of scrap at the Customer (per pound):

E(scrap cost) = $Q_{11} * P_1 * A_1 * T * D_1 + (1-Q_{11}) * Q_{12} * P_1 * A_1 * T * D_2$ (4-11)

Note that this is the sum of internal scrap costs plus the cost of metal scrapped at the customer.

Since the E(cost of a customer incident) = $(1-Q_{11}) * Q_{12} * P_1 * A_1 * T * D_2$ (4-12)

and

the E(cost of customer defect if identified in-house) = $(1-Q_{11}) * P_1 * A_1 * T * D_1$, (4-13)

we can calculate the E(Opportunity Cost of Missed Inspection (OCMI)) as

$(1-Q_{11}) * Q_{12} * P_1 * A_1 * T * (D_1-D_2)$ (4-14)

This value gives us an estimate of the COPSQ that could be reduced if the process had perfect inspection.

4.10.2 Multiple Defects, Multiple Process Steps

We can expand the above formulas (4-9 and 4-10) using some of our previously stated assumptions. We present recursive formulas that can be employed in any spreadsheet. The results presented in Section 4.12 utilize these formulas with the input spreadsheets shown in Figures 4-13, 4-14, and 4-16. First, define the following variables:

T_j = good pounds entering PC j
R_{ij} = pounds with defect i entering stage j or introduced at stage j
S_{ij} = pounds with defect i scrapped at PC j
F(j) = maximum defect index introduced before PC j

Then, we can write:

$$T_j = T_1 \prod_{i=1}^{F(j)} (1 - P_i A_i) \tag{4-15}$$

$$R_{ij} = (R_{i,j-1})(1 - Q_{i,j-1}), \quad \text{for } i=1,2,\ldots,F(j)$$

$$\text{or} \tag{4-16}$$

$$R_{ij} = T_j P_i A_i, \quad \text{for } i=F(j)+1,\ldots F(j+1)$$

$$S_{ij} = R_{ij} Q_{ij} \tag{4-17}$$

We can then write expressions for the COPSQ and OCMI as follows:

$$E(\text{COPSQ}) = \sum_{j=1}^{N} \sum_{i=1}^{M} S_{ij} D_{ij} \tag{4-18}$$

$$E(OCMI) = \sum_{j=1}^{N-1} \sum_{i=1}^{M} R_{ij}(1 - Q_{ij})(D_{i,j+1} - D_{ij}) \tag{4-19}$$

4.11 Rivertown COPSQ Computer Model Overview

This section describes the system of computer programs utilized to collect the data and produce model runs using the recursive formulas described in the previous sections. As indicated above, the input data for this model comes from a variety of original sources. All of the in-plant data ends up in a SCRAP file where there is one record per scrap incident and a CLOCK file where there is one record for every coil processed through each PC. Customer return data is stored in a RETURN file.

These files and several cross-reference tables (XREF) are accessed by a VAX/VMS FOCUS program that calculates values for test capabilities, defect generation, and fraction of pounds defective. The output files are downloaded through a Local Area Network (LAN) to a PC. From here, several EXCEL macros are run to manipulate the data into input spreadsheets in the form of those in Section 4.9. Finally, the OUTPUT EXCEL macro runs to create the output shown in Section 4.12. OUTPUT asks the user to specify the product type (to determine scrap costs) and run size (throughput) and then runs through the recursive formulas to compute Expected Values of COPSQ and OCMI.

Figure 4-18 shows a schematic of this computer system. The shaded areas were data files or programs created for this effort. Copies of code listings and original data remain on file at NAC.

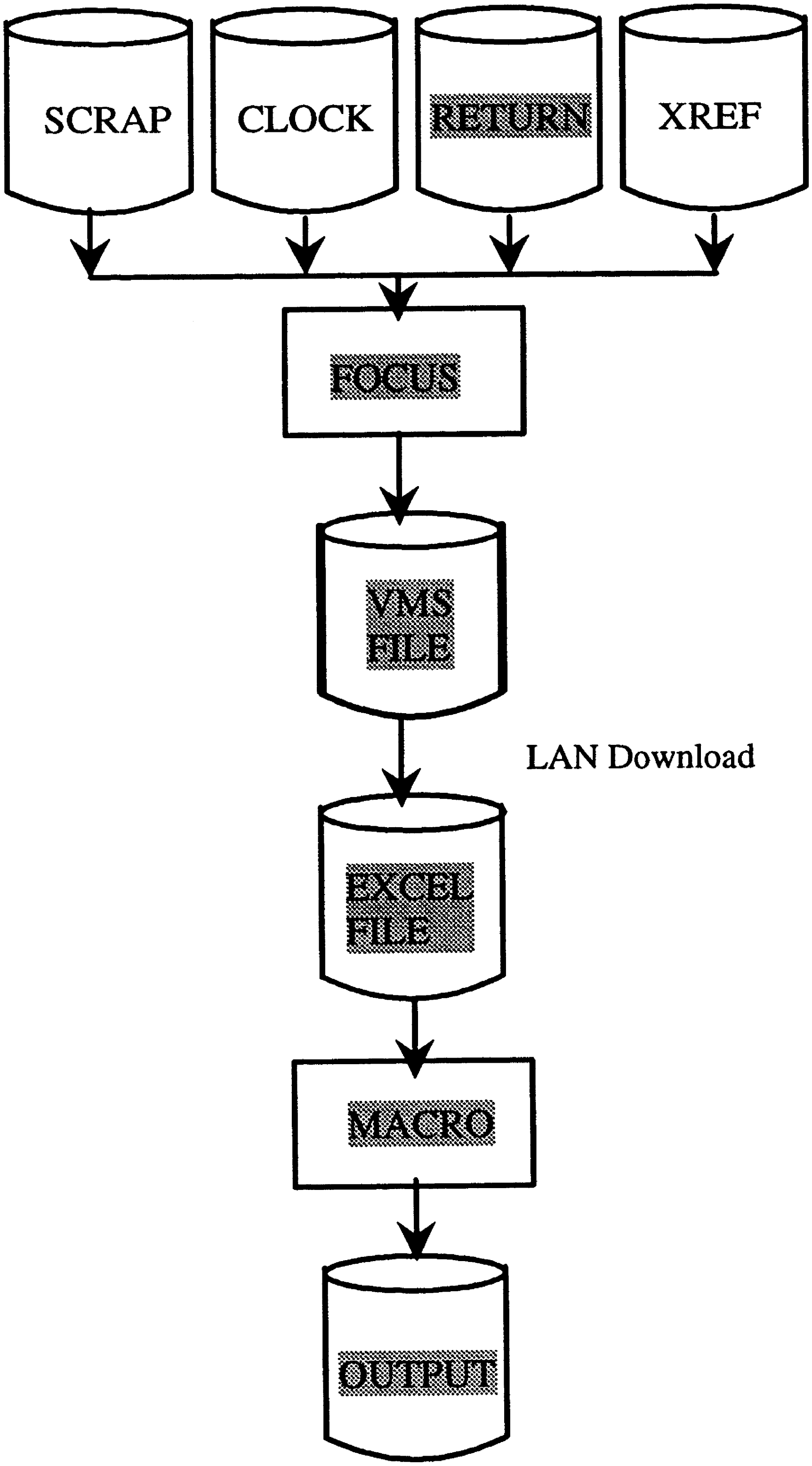


Figure 4-18. Schematic Diagram of COPSQ Computer System

4.12 Sample Model Output and Descriptions

The output of the computer system described in the previous section (for the input spreadsheets described earlier) is a single spreadsheet as in Figure 4-19. This spreadsheet can provide a wealth of information about expected results of changes to underlying parameters in the defect flow/inspection system and also serves as a useful format for purely descriptive presentation of COPSQ numbers. (Note that all of the input spreadsheets used in this model run contain disguised data.)

PC	**Defect 1**	**Defect 2**	**Defect 3**	**Defect 4**	**Defect 5**	**Defect 6**	**Total Scrap**	**Good Pounds**
			Coils with Defect					
Hot Mill	0	1	63	0	0	0		
Cold Mill	0	1	63	0	1	0		
Coater	0	1	63	0	1	0		
Customer	0	0	0	0	0	0		
			Scrap Pounds				0	35,000,000
Hot Mill	3,478	13,167	3,281,250	0	0	0	3,297,895	30,582,021
Cold Mill	0	0	0	9,509	871	0	10,380	29,451,267
Coater	0	0	0	0	0	72,659	72,659	28,258,234
Customer	0	26,334	1,093,750	0	290	0	1,120,374	27,137,860
	3,478	39,501	4,375,000	9,509	1,161	72,659	4,501,308	
			Defective Pounds Out					
Hot Mill	0	26,334	1,093,750	0	0	0		
Cold Mill	0	26,334	1,093,750	0	290	0		
Coater	0	26,334	1,093,750	0	290	0		
Customer	0	0	0	0	0	0		
			Scrap Costs					
Hot Mill	716	2,712	675,938	0	0	0	679,366	
Cold Mill	0	0	0	2,054	188	0	2,242	
Coater	0	0	0	0	0	192,619	192,619	
Customer	0	73,472	3,051,563	0	809	0	3,125,844	
	716	76,184	3,727,501	2,054	997	192,619	4,000,071	
			Opportunity Cost of Missed Inspection					
Hot Mill	0	263	10,938	0	0	0	11,201	
Cold Mill	0	64,123	2,663,281	0	706	0	2,728,110	
Coater	0	3,660	152,031	0	40	0	155,731	
Customer							0	

0	68,046	2,826,250	0	746	0	2,895,042

Figure 4-19. Rivertown Surface Inspection Cost Model Sample Output

Based on the information in the above spreadsheet, we may draw some conclusions about the current flow of surface defects for this product.

By examining the "Scrap Pounds" and "Defective Pounds Out" matrices, one can trace the flow of particular defects through the process. For example, Defect B results in a total of 39,501 pounds of scrap (for the arbitrary input of 35,000,000 pounds of metal). Note that 13,167 pounds is scrapped at the Hot Mill, while the remaining 26,334 defective pounds flow through the Cold Mill, through Coat-2, and ultimately to the Customer.

The bottom and right sides of each matrix show totals. This allows us to view the total scrap pounds and costs by defect and processing center. Finally, the OCMI matrix utilizes the formula (4-5) in Section 4.10.1 to calculate the additional scrap costs incurred because an amount of defective product flowed through an additional step in the process. The column totals of this matrix reflect the failure costs that could be saved if all occurrences of a particular defect were identified at the point of generation.

The above output points out some of the limitations of the expected value model presented in this thesis.

1) Only expected values are shown. Variance of pound or dollar amounts cannot be calculated.

2) If the model is run with only a subset of all possible reasons for scrap, one must be careful how to interpret the "good pounds" section of the "Scrap Pounds" matrix. Suppose, for example, that in this case, the six defects shown are the only surface defects in the plant. In addition to this scrap, however, processing centers each take 10% of the entering weight as planned trim during the process. In this case, we do not have an accurate "mass balance" since the above model ignores the additional scrap. As the purpose of this model is to estimate the COPSQ and OCMI, however, one may make the argument that the numbers as shown are quite useful.

If we assume that the term "Good Pounds" refers to metal that will not be taken as trim scrap, and that we should not include in the Failure Costs defective metal that would be scrapped anyway, the dollar estimates shown will be accurate. We must remember to "scale-up" the pound amounts to include all other scrap if we wish to report actual entering and exiting pounds.

3) As the "Coils with Defect" matrix shows, the model does not remove coils once they have been marked as defective. Since many "Whole Coil Scraps" at Rivertown are actually only partial scraps (and the incident rates are very low) this may not be a poor assumption. In general, however, it will overestimate the number of coils that flow out of the process. The pound total does get updated, however, so it will not reflect this error.

By changing the numbers on the input spreadsheets shown in Section 4.9, we can model the impact of changes in defect generation rates or inspection capability on the overall COPSQ and OCMI as well as on the performance of particular processing centers. This is the subject of Chapter 5.

Chapter 5 -- Use of Model for Inspection Planning

5.1 Methodology for Reduction of COPSQ

The model presented in this thesis can be used as part of a structured methodology to reduce the overall COPSQ at a manufacturing facility. Section 5.1.1 presents a graphical interpretation of such a methodology. Section 5.1.2 addresses reduction in COPSQ through reduction in the rate of generation of surface defects. Section 5.1.3 provides some guidance in the use of the model presented here for Inspection Planning. Finally, Section 5.1.4 compares a simulation approach to modeling defect generation with the expected value approach emphasized in this work. This comparison illustrates the major limitations of the expected value approach and provides insight for modeling repeating defects.

5.1.1 Graphical Presentation of Methodology

Figure 5-1 shows a global approach to the reduction of COPSQ. It involves the identification of process or inspection enhancements with positive Net Present Value (NPV) that will reduce the COPSQ.

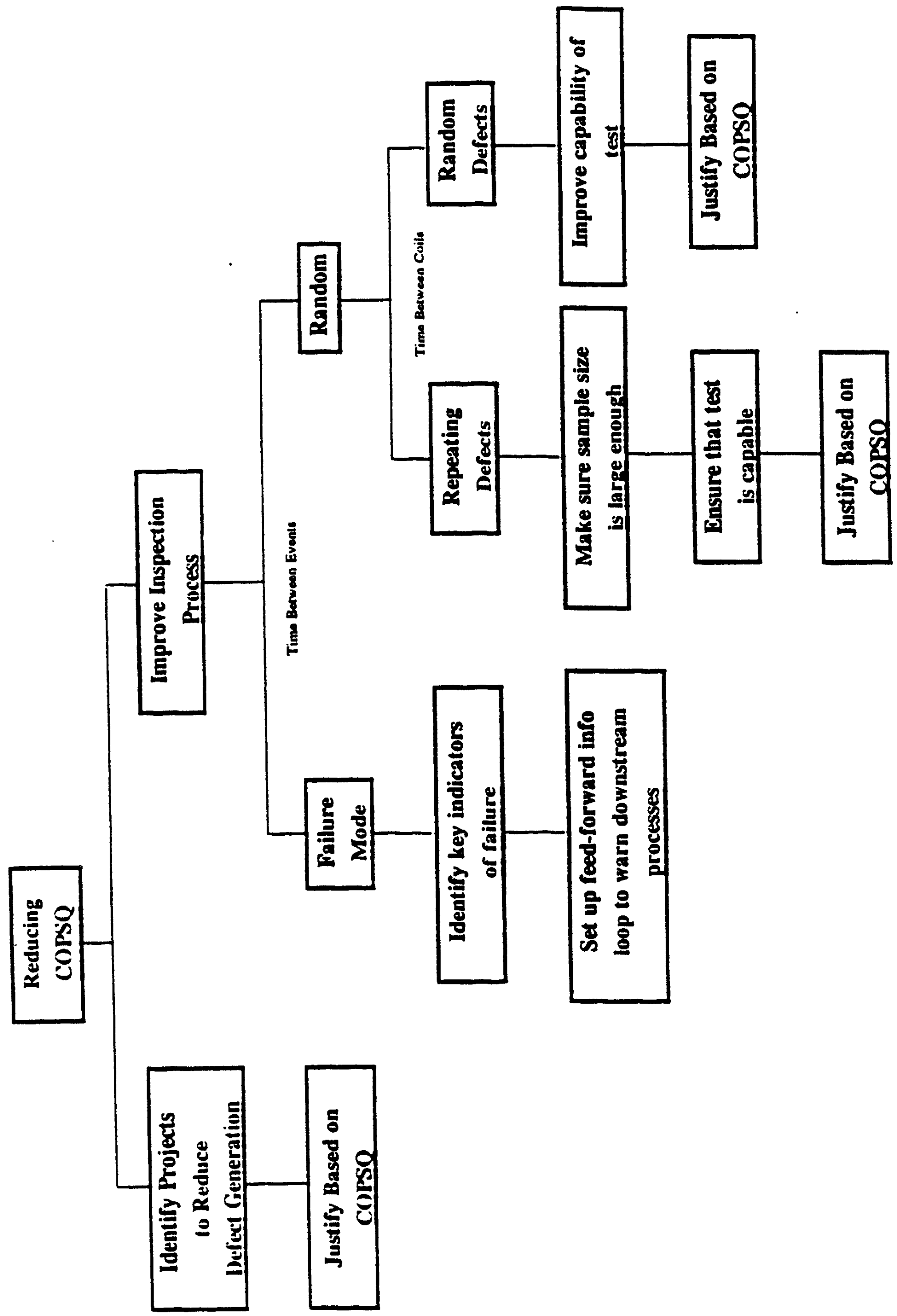


Figure 5-1. COPSQ Reduction Methodology

5.1.2 Reduction in Rate of Defect Generation

Reducing defect generation begins with identifying the root causes of product variability as illustrated conceptually in Figure 2-5. Given the specific objectives of the project problem statement, we have chosen to not model such improvements at a detailed level for this thesis, but re-emphasize the claim made in Section 2.4.2 that the long-term goal of an organization should be to minimize process variability *and* inspection.

5.1.3 Inspection Planning

We may not be able to immediately identify all possible process improvements to address underlying variability, or we may face serious human or capital resource limitations that prohibit the undertaking of complex process improvement projects. In these instances, increasing customer attention to quality may require a focus on improving the inspection process to continue to satisfy our customers' definitions of "Perceived Value."

In this case, we should first decide whether the defects in question are related to a specific failure mode in the process or are random in their distribution of Coils Between Events (CBE). We can make such a judgment by comparing an empirical distribution of CBE obtained from current scrap data to the exponential distribution that would be achieved if the event of a defect were truly randomly distributed. (This was described in Section 4.7.) If the defect is correlated to some failure mode, we must attempt to locate the source of the failure and create preventive maintenance procedures to minimize the number of failures. In addition, as the chart shows, we should set up mechanisms to inform downstream processes of failures should they be detected after some metal has been processed.

Random CBE defects can be separated into repeating defects (like roll marks, solution stains, bruises, scratches, dents, etc.) and random defects. Repeating defects are easier to identify as only one observed occurrence of the defect on a given sampled coil is needed. (This assumes that we have capable inspection!) Our problem then becomes one of optimizing the tradeoff between destructive sampling (if it is necessary -- in fact, at the cold mills, we peel back most coils anyway) and exposure to producing defective product between samples. The calculation for sample size is straightforward and shown in the following paragraph for the Cold Mill exit end inspection.

Rivertown cold mills are composed of five or six sets of stands as shown in Figure 2-3. Each time the sheet passes through a stand, it is reduced in gauge. Thus, simple geometry tells us that a defect that is i inches long before stand one will be R_1*i (inches) long where R_1 is input gauge/output gauge of stand one. As each successive stand will result in a reduction of R_j, we can see that a defect that starts out at i inches before stand one will be $iR_T = i\prod_j R_j$ after T stands. For example, for a defect caused at the Cold Mill stand one, we simply multiply R_T by the circumference of the largest roll used in stand one to calculate the sample size that we must take to ensure that we identify all repeating defects. For Rivertown's cold mills, the correct sample size is 60.25 feet.

After the correct sample size has been verified (Rivertown's cold mills take 60 feet of inspection scrap) we must ensure that the test itself is 100% capable. If it is not, then any analysis of the optimal tradeoff between exposure and sample frequency as discussed in Section 3.2 will not be valid.

Finally, if the CBD distribution is shown to be random as in Figure 4-7 , we must improve the capability of our tests or pay for a step change in technology to achieve our desired results.

5.2 Modeling Reduction of Defect Generation Rates

The results of model runs for several products are presented graphically in two key forms. Figure 5-2 shows the Cost of Poor Surface Quality (COPSQ) vs. a fraction of current defect generation rates. The predicted change in COPSQ decreases more for proportional increases in all Hot Mill versus Cold Mill surface defect generation rates. In other words, by holding the test capabilities and pounds/incident constant, one sees larger gains for this product from reducing the generation rate of Hot Mill defects.

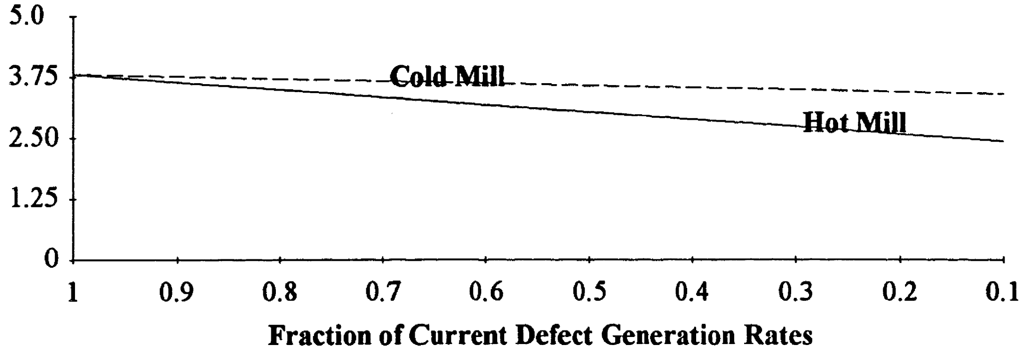


Figure 5-2. COPSQ as a Fraction of Current Defect Generation Rates for Product 1

Figure 5-3 is the second type of graph where more detail regarding individual PCs, includes coating PCs, is presented. (Note that Figure 5-3 also separates the data into products that flow through Coat-1 versus those that flow through Coat-2.) Here we observe first that the average COPSQ for Coat-1 is higher than for Coat-2. This is a fundamental advantage that is often cited by proponents of the Coat-2 system. It remains to be seen what impact current process control efforts will have on this distribution.

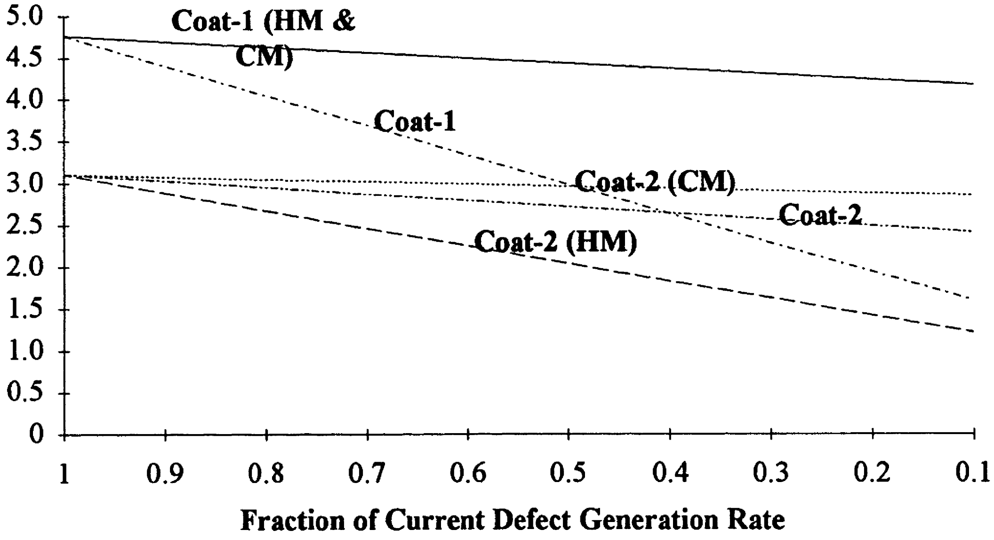


Figure 5-3. COPSQ as a Fraction of Current Defect Generation Rates for Individual PCs

Figure 5-3 also shows that relatively little can be gained from lowering cold mill generation rates.

5.3 Modeling Improvements in Inspection Capability

To model changes in the existing inspection system, we hold defect generation rates constant and vary test capability. Similar to the previous case, we can simply multiply all test capabilities for a given PC by a constant factor (this time greater than one) to predict COPSQ. Figure 5-4 shows the results of such model runs with Hot Mill and Cold Mill Test Capability varied. We note that, again, the large gains can be made by improving the processes at the Hot Mill. This time, we require only a 25% increase in test capability to achieve significant reduction in COPSQ.

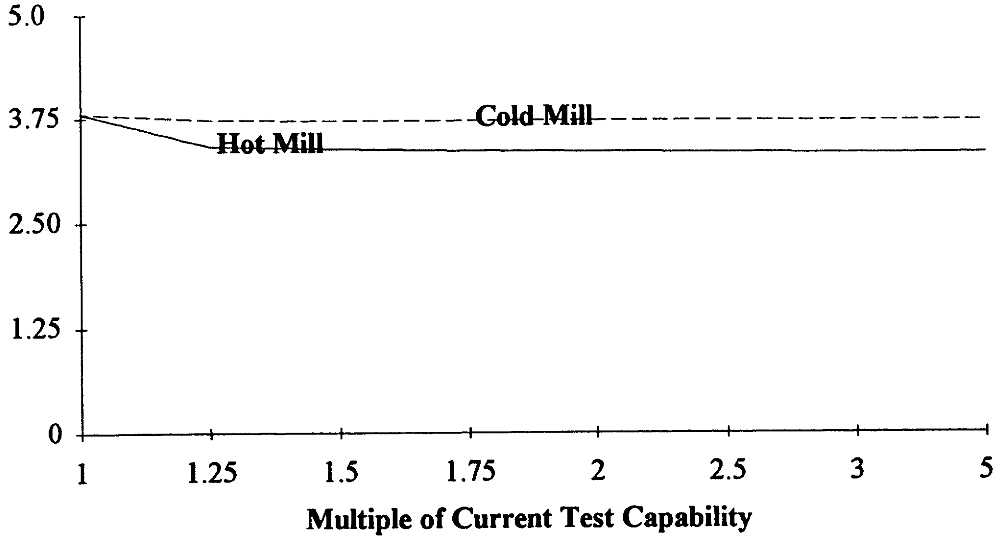


Figure 5-4. COPSQ as a Multiple of Current Test Capability for Product 1

Figure 5-4 suggests that there will not be any gain by improving the Cold Mill inspection process. This may be true if we consider only the defects that we can currently *see* with the human eye. (Any which started with a test capability of zero will not improve.) We might want to consider step changes in technology or inspection conditions that may allow us to see other defects. In this case (which we will consider below) we will need to change some of the test capabilities to a non-zero value.

Figure 5-5 shows the detailed effects that lead to the results given in Figure 5-4 and includes trials for changes in Coat-1 and Coat-2 inspection. Note here, again, that Coat-1 has a significantly higher COPSQ than Coat-2. The only real advantage to be gained from enhancing existing inspection by a proportionality constant lies with the Hot Mill increase noted above. This graph merely points out that the bulk of the potential reduction in COPSQ will come from Coat-2 product.

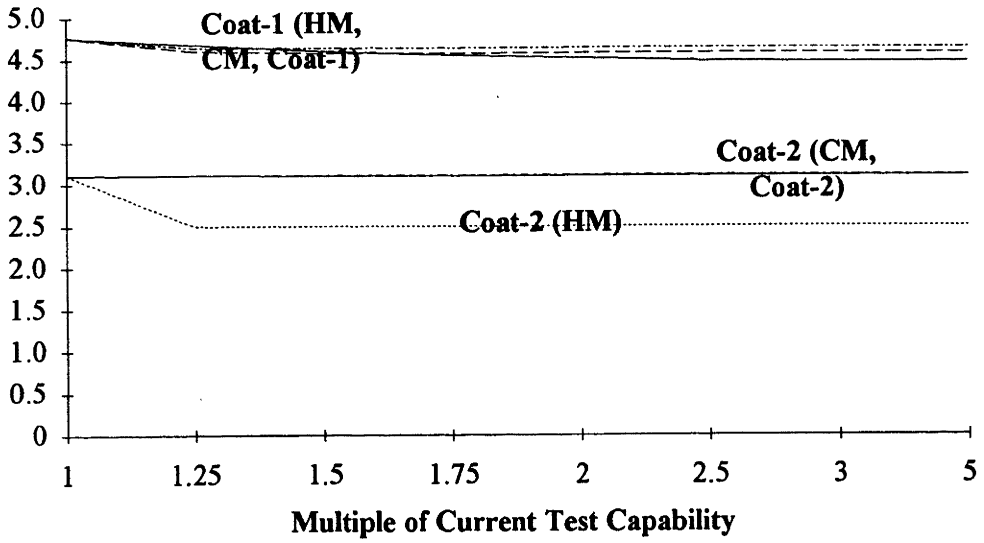


Figure 5-5. COPSQ as a Multiple of Current Test Capability for Individual PCs

Quite unexpectedly, increasing the test capability at the coating lines does not lower costs. This is because most of the coating and mill related defects are caught before they reach the exit end of the coating lines. Those that are missed are essentially beyond the capability of the tests to identify them.

Figure 5-6 shows a slightly different way of looking at this inspection/quality problem. Here, we plot the opportunity cost of missed inspection as a fraction of COPSQ. Note first that for Coat-2, Opportunity Cost of Missed Inspection (OCOMI) is 53% while Coat-1 is currently at 13%. Even though Coat-2 has a significantly lower COPSQ, it has a much higher OCMI. (Remember that the OCMI shows the reduction in COPSQ that could be obtained if we had perfect inspection.) This chart clearly shows that Coat-2's Hot Mill related defects are the largest cost of our current inspection system.

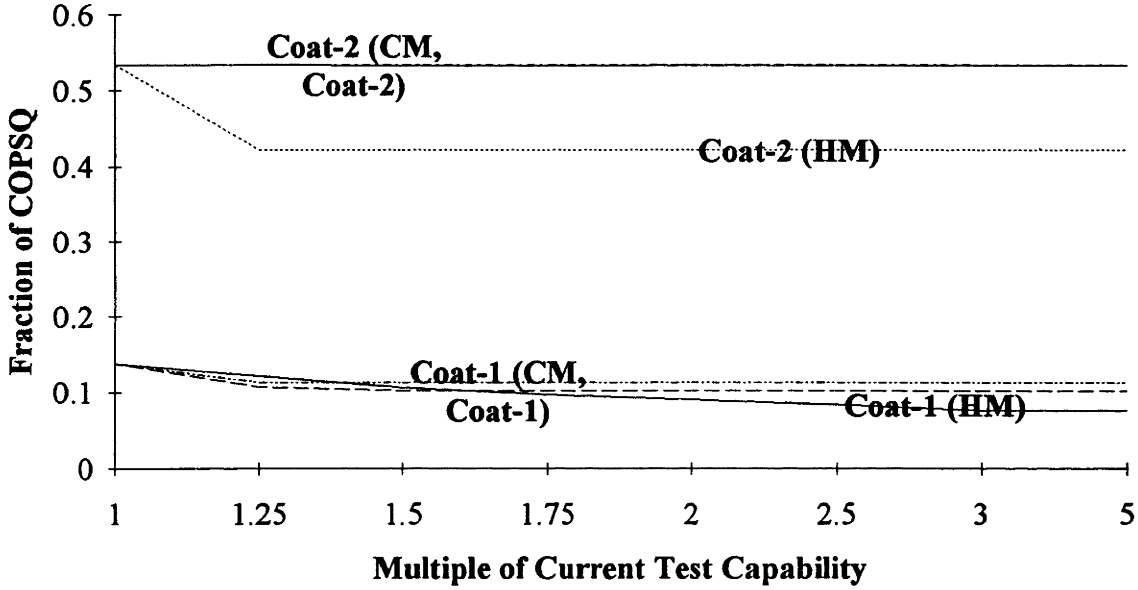


Figure 5-6. OCMI as a Fraction of COPSQ vs. Multiple of Current Test Capability

Modeling the impact of changes in test capability on COPSQ and OCMI seems quite straightforward; however, tying these results to underlying changes in inspection frequency or sample size is more difficult and requires additional calculation. The following definitions apply to the discussion that follows:

p = probability that a human being will see a particular defect during testing
l = length of sheet inspected
L = total length of sheet
F = period of inspection (in coils)
q = probability that we identify a defect if it exists

Assuming that defects are randomly distributed across the sheet so that we do not need to include location specific variables here, we may write:

$$q = p * (l/L) * (1/F) \quad (5\text{-}1)$$

So, we can estimate the new probability of identifying a defect (due to an adjustment in sampling frequency or size) by:

$$C_2 = C_1 \frac{l_2}{l_1} \quad (5\text{-}2)$$

or

$$C_2 = C_1 \frac{F_1}{F_2} \quad (5\text{-}3)$$

This approach does not allow the user to estimate the change in expected value of COPSQ or OCMI for purely repeating defects (those related to failure modes in the process.) For these, scrap will continue to be generated in every coil after the first one until the defect is found. The best way to model changes in inspection frequency here will be to alter the defect generation rate. This makes sense since an increase in inspection frequency will cause corrective action when a failure occurs to be taken earlier, resulting in fewer defects generated. Note that with the simulation approach to this problem shown in Section 5.4, modeling repeating defects can be much more intuitive.

5.4 Sample Simulation Output

Figure 5-7 presents a flow diagram of a sample simulation model. This diagram is different from Figure 4-10 because of the following assumptions:

1) All CBE distributions are random, hence we can treat coils going through

production centers as Bernoulli trials.

2) Test capability is characterized by one number which represents the probability that if a defect is present and the sheet is inspected, it is identified. Test frequency is handled explicitly.

3) This model includes preventive maintenance. This is extremely important for repeating defects because if preventive maintenance is performed before a defect is identified, even with perfect inspection "Capability" (when the sheet is actually examined), we may find defective metal getting to downstream PCs.

The logic can be repeated for multiple defects at multiple processing centers, but for simplicity was developed here for one repeating defect at one PC. The variables used in the diagram are defined below:

R(k) = 0 if there is no defect, 1 if there is a defect

D(t) = 0 if coil t has no defect, 1 if coil t has a defect

T(t) = 0 if coil t was not identified as defective, 1 if coil t was identified as defective

F(t) = the number of defective coils (including t) that went to the downstream process for the defect associated with coil t

M = preventive maintenance period in coils

C(k) = test capability (probability that if there is a defect it is identified during a test)

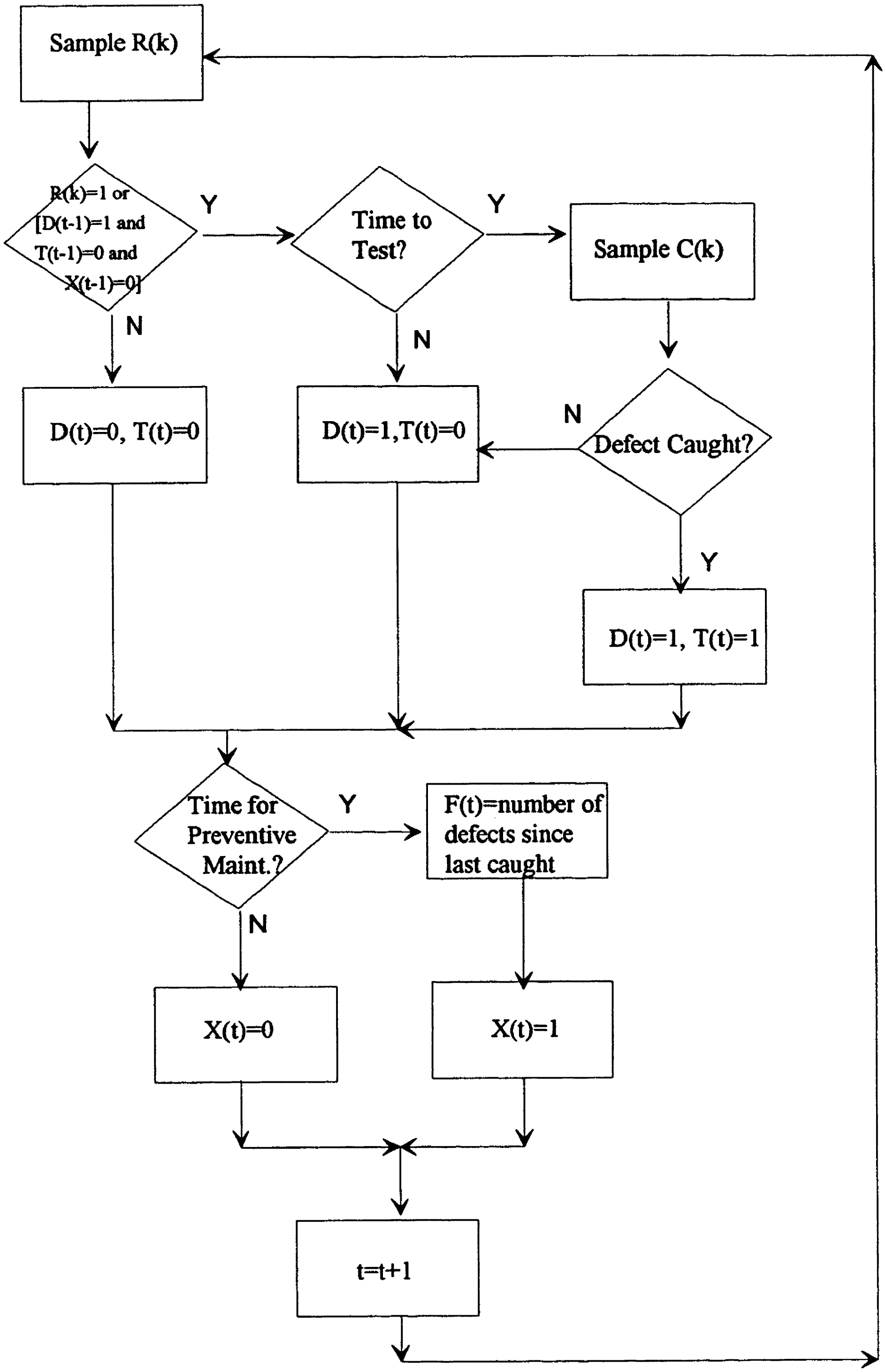


Figure 5-7. Flow Diagram of Example Simulation II

This model was programmed into an Excel spreadsheet and various trials (simulating the processing of 500 coils) were run. The base case is for a repeating defect where a good coil has a 25% chance of getting a defect (until failure occurs), the test capability is 90% (performed every 4 coils) and the preventive maintenance (a roll change for the cold mills) is done every 30 coils. Figure 5-8 shows a comparison of one simulation run with the results predicted by the expected value model developed in this thesis. Note that the models are in reasonable agreement (the variance of P as defined in Section 4.10.2 is 0.0035).

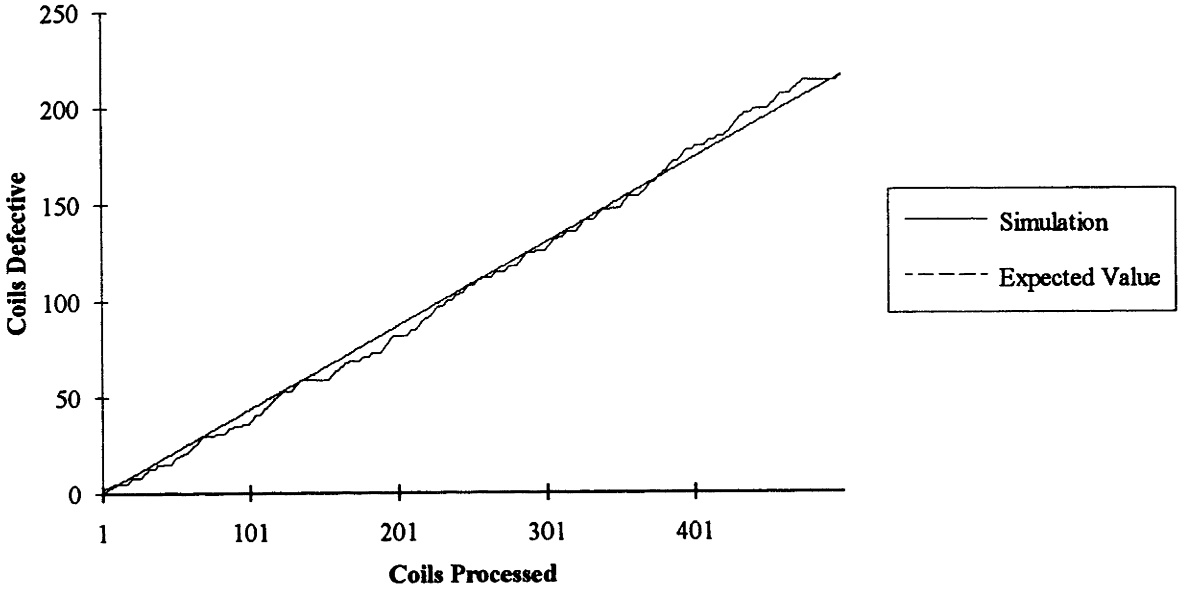


Figure 5-8. Simulation vs. Expected Value (R=0.25, C=0.9, M=30)

Figure 5-9 shows a similar simulation for a test capability of 50%. Note that again, the models are in agreement. As alluded to at the end of Section 4.7.2, the probability of defect generation was adjusted upward from 0.434 to 0.596 to keep the expected value model accurate. In fact, one might opt to use some simple models like this one to adjust the defect generation probabilities for repeating defects in the expected value model.

Unlike the run in Figure 5-8, this simulation produced some coils that made it through the inspection process and out to the downstream customer. The effective Q (as defined in Equation 4-2) that resulted was 0.886, and the variance of P was 0.0097.

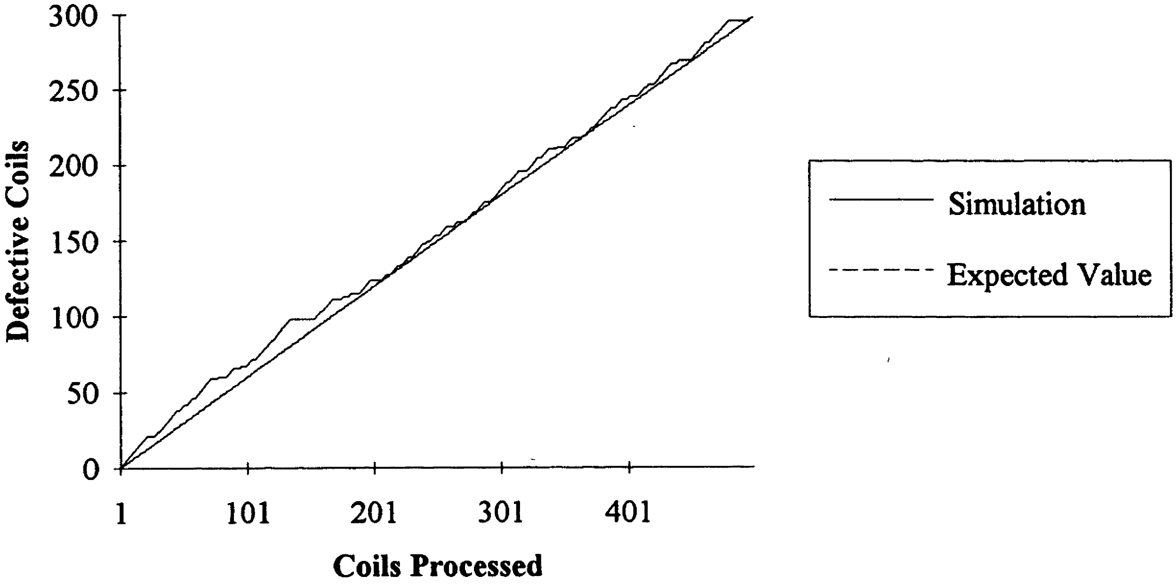


Figure 5-9. Simulation vs. Expected Value (R=0.25, C=0.5, M=30)

The run presented in Figure 5-10 alters the test frequency from every fourth coil to every second coil. This results in a new effective Q (0.90) and P (as defined in Section 4.7.2) that goes from 0.596 to 0.562 for the expected value model. Again, with these changes, the expected value model closely follows the simulation run with a variance in P of 0.015.

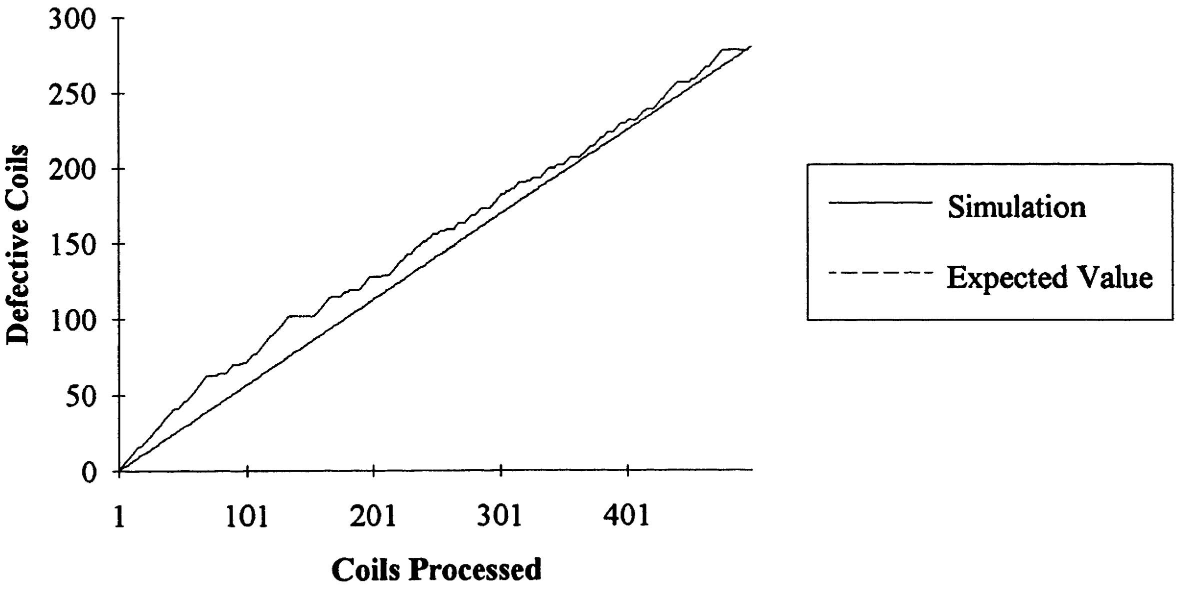


Figure 5-10. Simulation vs. Expected Value (R=0.25, C=0.5, M=30, test frequency = 2)

Finally, Figure 5-11 shows the number of defects that get to downstream PCs for the last model run. Note that due to the relatively small run size, there is significant difference between the models. Over relatively long time periods, the expected value of the simulation results and that calculated by the expected value model will be close. However, the expected value model will fail to capture the large variance that the simulation uncovers: a variance that exists in real life and is currently a major concern of plant management.

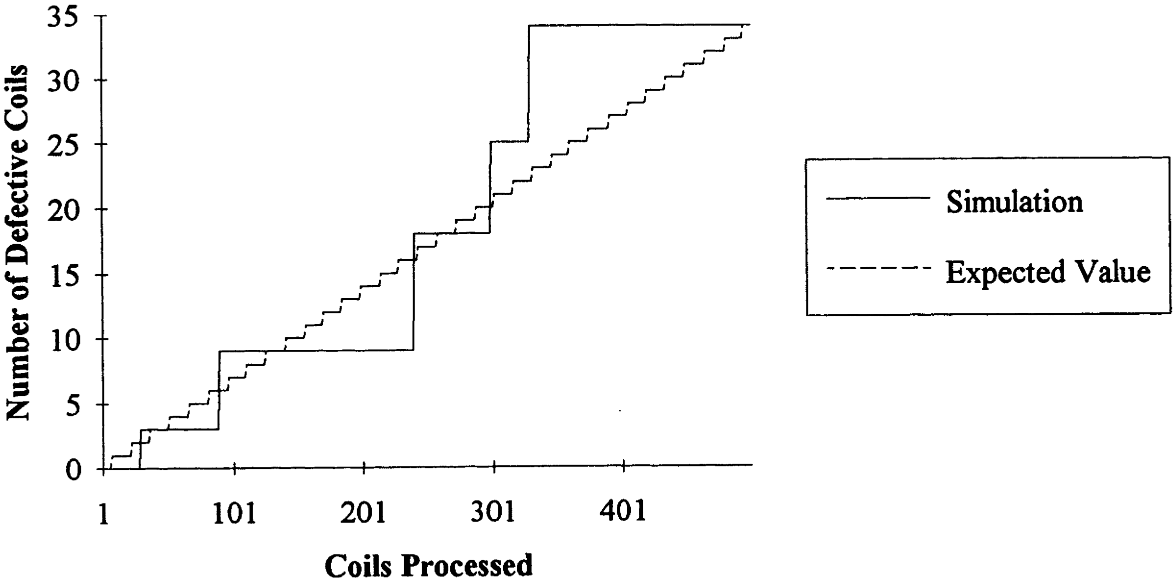


Figure 5-11. Number of Defective Coils Getting Through to Downstream PCs (R=0.25, C=0.5, M=30)

5.5 Modeling Step Changes in Inspection Capability or Location

Figure 5-12 below shows the results for the step change in technology or technique mentioned in Section 5.3. Here we have changed the test capabilities at the Cold Mill in the following manner:

i) For defects with a current test capability greater than zero, we assume that a new inspection system will identify all defects (i.e. a test capability of 100%.)

ii) For defects with a test capability equal to zero, we increase this capability in 25% increments ending with a 100% test capability for all Hot Mill and Cold Mill defects.

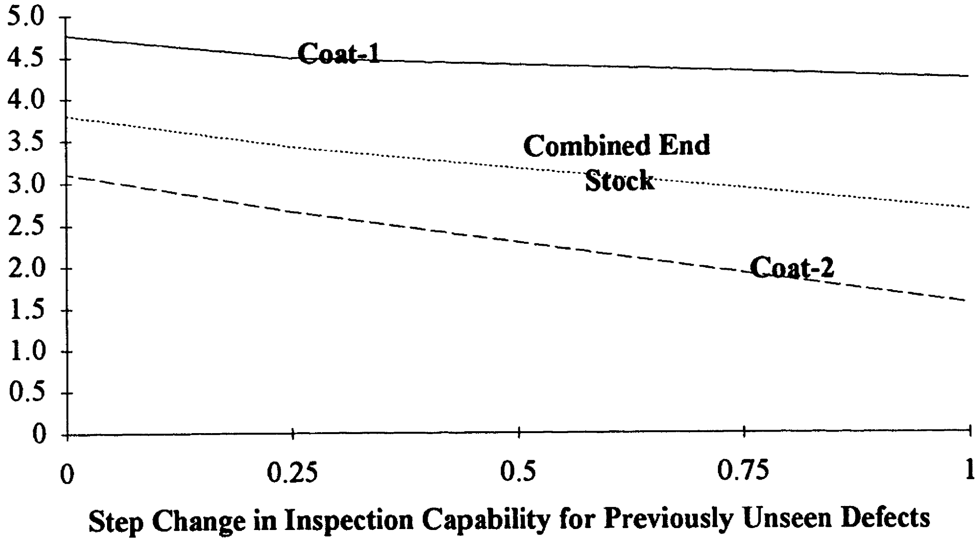


Figure 5-12. COPSQ for Cold Mill Inspection System with Step Changes

Assuming that we can design or purchase such a system, we can dramatically reduce COPSQ. This reduction amounts to almost the same savings that would be achieved by the reduction in Hot Mill defects presented in Figure 5-2. It seems, at least in this case, that the choices are clear. To reduce the COPSQ for the Coat-2 product in particular, we can either eliminate the source of the defects, or put an inspection system that is extremely capable *before the bottleneck*.

Chapter 6 -- General Observations and Recommendations

6.1 Suggested Inspection Changes

Before suggesting specific changes in the inspection system to lower COPSQ, I want to emphasize that variability reduction is the only viable long-term strategy for improved quality. Everything else will result in a cost structure that is inherently higher than the optimum for a given process. As the length of time for sustainable competitive advantage due to process differences is becoming much less than National Aluminum Company (NAC) has historically been accustomed to, it must learn to rely more on rapid process understanding to achieve high quality.

As has been mentioned before, in the short-run, when quality to the customer must be maintained, inspection serves the dual role of removing bad product from the system and providing feedback regarding product and process quality. The model and methodology developed in this thesis has suggested specific changes for the Rivertown management to consider to improve the overall surface inspection system. These include:

1) Improve capability to identify repeating defects to 100% at the Cold Mill. As the sample size has been shown to be long enough, it is wholly unacceptable to miss defects like roll marks, lube stain, and solution stain during inspection at the exit end of the cold mills. (As discussed in Chapter 5, an inspection prior to a roll change will ensure that no defective metal gets downstream.)

2) Improve the capability to identify Hot Mill defects before the bottleneck (particularly for Coat-2 products.) Both 1) and 2) may be helped by some low capital changes that have been suggested by Rivertown personnel including:

   - an elevated, lighted inspection station (it does not require all of the capital expense that went into the station at Rivertown's sister plant).
   - education for both Cold Mill supervisors and operators about the appearance of Hot Mill and Cold Mill Defects.
   - inclusion of operators in inspection at Cold Mill. Quality should be part of the job description and behavior of a mill operator.

   Also, the plant should consider capital investment in an automatic inspection system at the exit end of the Cold Mills (especially the cold mill where most of the wide Coated End stock runs.) Though the speeds here and vaporized lubricant make the conditions tough, several technologies exist to drastically improve the capability of Cold Mill inspection. Rivertown should consider looking to producers of other products that travel in a web at high speeds for help. Such producers include the paper and photographic film industries.

3) Increase inspection capability of Hot Mill inspection. This could include the following:

   - increase the frequency of continuous mill samples or other visual or destructive inspections that we are certain are correlated to surface test capability.
   - examine continuous mill peelbacks very carefully for Hot Mill defects.
   - educate operators on the appearance of Hot Mill surface defects and build incentives for quality into job descriptions and performance pay.

6.2 Suggested Information System Changes

Work on defect reduction and inspection optimization demands accurate and timely data. Though Rivertown is working hard to improve the availability and accuracy of inspection and process data there is room for improvement. Some suggestions for managing and processing defect data in general follow:

1) Improve the data base/information system design, development, and implementation methodology to be more standardized and to include rigid testing at the module and system level. It is not acceptable to let end users operate with incorrect data as a form of "final test."

2) Develop and publish a strategic plan for information systems. Decide which mainframe, Local Area Network (LAN), and distributive processing systems will be utilized in the future and work to get users moving in the right directions. Rather than maintaining support and data on three different database access systems, pick one as the suggested platform and get all users migrated as soon as possible.

3) Require that users spend some time helping to plan their data requirements over the next several years. If an adequate plan is not developed, the Data Warehouse Concept (a central repository for process and product management data) will quickly become unmanageable.

4) Include customer clocking and return information in all production files. The end customer is simply the last "machine" in the production process and should be treated as such. This will require the consolidation of some codes and cross reference tables that will make communication between plant quality experts and production managers much easier.

5) Consider cross-training young engineers and information systems people. Perhaps an "internship" or part-time assignment alongside an Information Systems analyst would help produce knowledgeable users for the future.

6) Develop an audit procedure to ensure that people are not just entering numbers to get onto the next coil to be processed. The new "metal balance" screens only ensure that all pounds of metal are accounted for. They do not ensure that shop floor personnel are accurately recording defect information.

7) Consider tracking "near misses" with the parabolic loss function shown in Figure 3-1 in mind. There is a hold system available that records instances where metal is "held" for further inspection. Tracking occurrences of holds may help predict when quality is beginning to decay, but not yet out of specifications.

6.3 COQ System Development and Organizational Implications

By considering the development and implementation of a COPSQ system at Rivertown, I can make some observations about the practicality of incorporating such systems in other plants with well established quality or yield metrics.

1) Simple systems reporting out-of-pocket expenses for failures (COPQ) can dramatically alter perceptions. Though it may seem to the outsider to be completely obvious that a focus on yield is not the same as a focus on reducing COPQ, plant personnel long accustomed to the same metrics may not find it so obvious. The key word here, in any event, is simple. Much of the criticisms of early COQ systems were right on: if one is not careful they may actually cost more than the savings they bring. Another burdensome cost accounting system is not desirable for any plant.

2) COQ should incorporate failure costs for defects that occur at the end customer as these may be significant. Though it may be tempting to ignore these costs, doing so only encourages plant people to send suspect metal out the door in the interest of "yield" improvement. This suggestion may require the improvement of data systems as mentioned before and certainly calls for increased attention to quality surveys and customer feedback.

3) Over the long term, one should make attempts to value the impact of current quality on future purchasing decisions. This industry is a difficult one for that as the customer base is small and heavily dependent on NAC metal. In any event, the chance that any market share will be given away due to sustained quality deficiency is too risky to take.

4) Checks should be made that relative decisions are those that we "ought" to be making. This does not suggest that we ignore errors in reported cost numbers, only that we

> don't avoid doing the right thing because we are worried that cost numbers might be less accurate than the scrap data from which they came.

6.4 Team-based Implementation

The appropriate group to focus on COPQ is the same group that pushes for yield improvements. At Rivertown this is the Recovery Lead Team (RLT), and it was entirely appropriate to assign me to this team from the start. To carry this work forward, the RLT must aid and monitor the implementation of a system-wide approach to reduce COPQ. One person alone cannot possibly implement all aspects of such a program. Because it includes changes in information systems, inspection frequencies, shop floor behavior, performance incentives, and even potentially labor relations, a multidisciplinary approach where team members are informed of all activities is paramount.

6.5 Financial vs. Non-Financial Indicators -- Metrics

This is perhaps the most straightforward yet most complex of the recommendation categories addressed in this thesis. The straightforward part is this: recovery is a financial indicator so treat it as such. As has been shown in previous chapters, the dollar impact of scrap can be quite significant and not properly represented by a pounds-based recovery number. In addition, the impact of defects at the customer is completely ignored by an in-plant recovery number. Given traditional lead times, this is not surprising, but with the move to a reduced flowtime environment, it may be possible to include customer incidents in the reported in-plant numbers.

These arguments for financial indicators holds for other traditional metrics as well. For instance, measuring inventory on a pounds basis only encourages managers to hold the target inventory as close to finished goods as possible. For a plant where the finished product may have over 10 times the value added compared to an ingot, this will not necessarily minimize the costs of holding inventory.

6.6 Reduced Inventory or Environmental Changes -- COPQ Numbers Change

Two current trends that may impact the validity of decisions made with historical COPQ data are the move to reduced inventory and increasing market competitiveness. As alluded to in Chapter 3, the real danger in using aggregate numbers or ratios is that one may forget the assumptions and limitations on their use. Perhaps the biggest danger in creating complex information systems to report COPQ numbers is that people become attached to the output as it has always been. They begin to structure their behavior around management reactions to current numbers and lose their ability to criticize the underlying assumptions and uncertainties of the numbers.

The drive to reduce inventory often leads to increases in set-up scrap. This will adversely impact the COPQ, but may be the right thing to do. Conflicts between proponents of inventory reduction and backers of COPQ must be careful to consider the dollar implications of the tradeoffs they are advocating. The ultimate win-win is to find an approach like setup time and scrap reduction that leads to lower COPQ *and* lower inventory.

Increasing customer demands may cause a shift in the COPQ even further towards domination by external failure costs. As mentioned above, these costs already comprise a substantial portion of the COPQ at a plant like Rivertown. Ignoring these costs or failing to try to value the impact on future purchases of current quality may make the COPQ numbers less useful for decision-making and process monitoring.

Chapter 7 -- Future Research

7.1 Impact of Current Quality on Future Purchasing Decisions for Firms with Few Customers and Relatively Few Competitors

In the conclusions the importance of fully valuing the cost of failures at the customer was emphasized. In order to make COPQ reporting as accurate as possible, firms must make an attempt to value the full cost of current quality.

Some attempts were made in this work to use historical survey results to draw correlations between performance on quality dimensions and purchasing. Regressions were run with explanatory variables like lagged surface quality ratings, lagged overall quality ratings, and others. With only several years and very incomplete data, no statistically significant correlations were found, however.

The work on Relative Perceived Value Analysis being conducted currently by the Institute for the Study of Business Markets at The Pennsylvania State University may provide some assistance in developing effective data bases on perceived customer quality. Regardless of the tool used, however, management should attempt to get quantifiable and frequent customer feedback on a variety of dimensions of total delivered quality.

Future work could use this information to develop correlations between purchasing decisions and historical quality mentioned above. A difficulty for the aluminum industry is the relatively few numbers of customers and competitors. In this case, as was often pointed out by sales and marketing personnel at Rivertown, customers may enter into longer term contracts that go beyond the traditional price versus quantity tradeoffs of perfectly competitive markets.

7.2 Improve the Accuracy of Any Portion of This Model

The difference between an expected value model and a complex stochastic simulation can be a certain amount of accuracy that is compromised in favor of utility. As an organization like Rivertown becomes more comfortable with models like COPSQ, more accurate (if complex) data may be desirable. Relaxing some of the assumptions of an expected value model will make the model more closely resemble real life. A simulation-based model could take the accuracy even further.

7.3 Consider Optimization Model of Inspection System using COQ Framework

The model developed in this thesis relied on Monte-Carlo type simulation to suggest low-dollar changes in the surface inspection system. Earlier chapters pointed out that a COPQ system relies on an individual cost/benefit analysis of prevention projects to determine the optimal investments. Certainly the model presented here will aid in such analyses, but may require searching a large number of feasible solutions if many projects exist or capital becomes abundant.

In this case, an optimization model utilizing explicit formulas for COPSQ may be combined with formulas valuing the costs of various projects to produce an objective function to be minimized. Constraints relating to capital or project labor limitations, project dependencies, or other management objectives could be built into a linear or non-linear program.

This approach may prove to be quite complex and not of much use in a low capital environment, but certainly forms an important academic problem to be considered.

7.4 Compare Economics of Team Quality Training vs. Automatic Inspection Systems

This thesis suggests that large gains may result from quality training for workers and supervisors. Such benefits would come from improved process knowledge, better inspection capability, and higher overall awareness of the importance of creating a quality product.

On the other hand, an automatic inspection system that looks at 100% of the product (with current inspection often seeing less than 0.1% at the Cold Mills) may also drastically reduce the COPQ as shown in earlier chapters. Such an inspection system would require significant investment in the development of operating software, interfaces or tools for pattern recognition and root-cause analyses, and training for operators and engineers. In addition, the up-front capital costs of such systems can be prohibitive.

Deming would certainly say that this is no tradeoff. Only through increased awareness of quality by everyone can an organization successfully meet its customers needs. In the five-year time frame, however, some plants may find an investment in inspection (coupled with strategic investment in training) to be optimal.

7.5 Examine the Economics of Automatic Inspection Systems

Taken as a research interest by itself, the development of automatic inspection systems provides some interesting economics. Capital, software, and training costs are certainly important, however, several other economic factors should be considered.

First, the continual obsolescence of defect knowledge may prove to be quite costly. Part of an automatic inspection system may be the development of a knowledge base for pattern and defect recognition. Though this is attractive from an engineering perspective, the problem here is that when we solve a particular problem, the defect should not recur. Thus, we are constantly making our knowledge base obsolete (assuming again that we have truly addressed the underlying root causes of defects), which may create quite an information overload if the system is not developed carefully.

The second interesting economic issue is the option value provided by intermediate systems versus the sensitivity buffer provided by full-blown systems if customers get extremely selective. The challenge here is twofold. One, the capital investments in inspection technology should match the capability of the organization to use the information. There may be an option value in having some "excess capacity", but "bleeding edge" technology may simply cost too much. Two, the user of an automatic inspection system that "sees" all defects should be careful about leading customers to a non-functional and sub-optimal definition of product quality.

When taken down to the resolution of a scanning electron microscope, the surface of aluminum beverage sheet looks rough. For most markets, customers do not care about micron-scale imperfections in the sides and end of the can, hence there may be an optimal surface quality level.

7.6 Is Information Flow More of a Bottleneck than Production?

Future research may focus on the time constant for change of information systems versus the time constant that characterizes production initiatives like reduced flowtime, COPQ reduction, and process re-engineering. It is my opinion that quite often today data systems limit the ability of production systems to truly achieve their potential. Attempting to re-engineer a production facility, without total comprehension and expertise in the plant's data systems, may lead to fiscal suicide. Perhaps research could focus on case studies or on a detailed technical analysis of a single instance where information systems limited an organization's ability to follow management paradigm shifts.

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