An Integrative Approach to
Process Parameter Selection
in Fused-Silica Capillary Manufacturing

by
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Abstract

Process optimization requires identifying key processing input factors, determining their effect on the output of the process, and controlling these factors to produce the optimum response. Several models exist to help with this optimization, but focus on the direct response of the process or on the defined "quality" of the item being produced. Managers, however, must meet several objectives in optimizing the overall operation of the process, including revenue, cost, and service level goals. In this thesis we propose that selecting process parameter levels which optimize the process output while ignoring such factors as customer demand, costs, capacity requirements, revenues, and investments may lead to missed opportunities and a suboptimal manufacturing operation. We also propose that statistical models, in combination with economic models and operational analysis, can help in selecting those process parameter levels which improve the total operation.

The models proposed in this thesis were developed and applied during research at Hewlett-Packard's Avondale Site. Research focused on the process of drawing fused-silica capillary tubing. Through a combination of experiments and statistical analysis, we developed a predictive model which relates process parameter levels to the capillary strength. The experiments and analysis applied both the Taguchi Robust Design method and the Alkhairy parameter optimization method. The models also relate tubing strength to revenues for usable tubing lengths and to process yields. Through operational and cost analysis, we determine the process parameter effects on capacity, manufacturing costs, and necessary investments. Finally, we analyzed the group business strategy and market requirements in order to determine the combination of process settings which provide the greatest improvement relative to that strategy.

By selecting process parameter levels according to the integrative approach proposed in this thesis, the Hewlett-Packard columns group can expect the following improvements:

- 30% reduction in megabore capillary manufacturing costs
- Over $300K in annual cost savings
- Greater than 100% increase in drawing capacity on existing equipment
- Elimination of an immediate need for approximately $500K in capital equipment
- Capability to draw longer continuous columns and broaden the product line

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Chapter One
Introduction

1.1 Introduction

Industrial literature abounds with stories of manufacturing firms leapfrogging their competition through innovative product introductions. Companies devote research and development resources to developing the "home run" product which will improve their competitive position. Process improvements have not received as much attention, and many managers perceive the contribution of these improvements simply as incremental cost reductions. Hayes, Wheelwright, and Clark propose that improving and controlling manufacturing processes accomplishes much more than cost reductions or reliability improvements. They state that "process control creates the capabilities that build competitive advantage."¹ In evaluating a firm's process technology strategy, the same authors suggest that the strategy should ensure "that the firm's process technology evolves in a directed fashion, so that as technological capabilities are renewed and augmented, they reinforce and expand the firm's competitive position."²

Process optimization requires identifying key process input factors, determining their effect on the output of the process, and controlling these factors to produce the desired response. Several models exist to help with this optimization, but focus on the direct response of the process or on the defined "quality" of the item being produced. Figure 1-1 represents such a model. By concentrating solely on the direct process response, engineers will optimize the specific characteristic but may miss the opportunity to improve the overall

manufacturing operation and achieve a competitive advantage. Likewise, manufacturing managers must meet several objectives in optimizing a manufacturing operation including revenue, cost, and service level goals. Managers may fail to invest in process improvement efforts if they cannot foresee the impact that such improvements might have on meeting these goals.

![Diagram of Process Response Optimization]

**Figure 1-1:** Process response optimization. In the above figure, combinations of process parameters are chosen to optimize the direct process response.

The purpose of this thesis is to demonstrate an approach to process improvement which seeks to optimize the overall operation of a manufacturing center. We will show that:

1) Process parameters should be set not to optimize a particular process response but in a way that best meets the business strategy and needs of the operation;

2) The effect of process settings on the strategic goals can and should be predicted through the use statistical and operational analysis;

3) Improving processes through this integrative approach can produce dramatic strategic and economic benefits.

These points are illustrated through a process improvement example which substantially improved the competitive position of a Hewlett-Packard product group.
The integrative model developed in this thesis employs statistical methods to predict and control the process response. Operational and economic analysis enables the model to correlate process parameters and responses to strategic issues such as revenues, costs, and capacity. By incorporating the manufacturing center's business strategy and market environment, we can use the model to determine the impact of the process improvements. The integrative model is represented in Figure 1-2.

![Diagram]

**Figure 1-2**: Integrative process improvement. Process parameters are selected to optimize the competitive position.

In developing the predictive model which correlates process input parameters to the process response, we use two statistical process improvement methods. The first is Dr. Genichi Taguchi's Robust Design method, which engineers have used for several years. The second method is Dr. Ashraf Alkhairy's parameter optimization method. We will
show that both methods are very useful and practical tools for controlling and improving manufacturing processes.

1.2 Summary of Approach

Research which supported this thesis was conducted at Hewlett-Packard's Avondale Division in Avondale, Pennsylvania. The division manufactures equipment for gas chromatography (GC). The research project focused on the manufacture of fused-silica capillaries for use in analytical GC columns.

The research required the analysis of several aspects of the columns manufacturing center. The primary analysis required identifying and measuring critical process responses and process input parameters. We designed and performed an experiment around these variables, collected data, and used the two previously-mentioned statistical methods to improve and predict capillary quality. We then developed a methodology and computer program to relate quality improvements to incremental revenues.

The second stage of research included measuring operational elements such as process throughput, set-up and changeover times, run times, equipment utilization and staffing, and scrap. This analysis was needed to determine the general effect of process parameters and potential improvements on capacity, equipment needs, and manufacturing costs.

A third area of research involved analyzing the manufacturing costs of the capillaries. We studied the cost breakdown for the various capillary sizes and the contribution of capillary costs to the overall column cost. In addition, we determined the incremental costs associated with various settings of process parameters. This research
enabled us to assess the potential cost savings from improving the process and the impact of such savings on HP's columns business.

A fourth effort researched the columns group's strategy, competitive position, and options for addressing its needs. We studied the columns market and competitors, the relative strengths and weaknesses of Hewlett-Packard's position, and general issues of vertical integration. We also assessed a potential capillary supplier, investigating their capillary quality, costs, and the possibility of HP's divesting its capillary drawing operation. Through this analysis, we could address the strategic needs of the columns group and determine how process improvements could help to meet these needs or help the columns managers to choose between options for meeting the strategic objectives.

1.3 Thesis Organization

We have described the major research efforts which were necessary for developing this thesis. We will now review the organization of the thesis. Chapter Two provides an overview of Hewlett-Packard's Avondale Site, concentrating on the GC capillary columns business unit. It relates the invention of fused-silica capillary columns and describes the capillary drawing process on which we focused our process improvement efforts. An examination of the GC columns market precedes a discussion of the HP columns group's strategy for improving its market position. A discussion of HP's options for implementing its strategy follows.

Chapter Three details efforts to develop a statistical model which predicts the performance of the capillary drawing process. The chapter first presents a general overview of the Taguchi and Alkhairy methods of process optimization. A detailed discussion of the experimental design used in both methods follows, addressing the choice
Chapter 1

of process responses and process input parameters, and the tradeoffs involved in final experimental layout. The chapter then presents the experimental results, specifying the process settings which optimize capillary quality. The chapter ends with a discussion of the regression analysis used to predict capillary quality from the process parameters.

Chapter Four describes the development of the models which make up the integrative approach to process parameter selection. The chapter first discusses how capillary quality affects column revenues and influences product line expansion. It next describes how we correlate process parameter levels directly to production capacity and manufacturing costs. We then recommend a process parameter combination which best addresses the columns business strategy. Finally, the chapter presents the expected benefits of the proposed process changes and the important strategic advantages which they afford to the columns business.

Chapter Five provides a summary of the results of this thesis. It specifically reviews the integrative approach to process improvement, including a look at the substantial benefits Hewlett-Packard realized from the process changes.
Chapter Two

HP Avondale Columns Group

2.1 Introduction

Research which led to the integrative parameter selection approach presented in the previous chapter was performed at Hewlett-Packard’s Avondale Site in Avondale, Pennsylvania. In order to better understand the operational and strategic issues which influenced decisions in the integrative model, it is important to understand the competitive environment and history of the Avondale Site, particularly the analytical columns group. This chapter provides an overview of the division and the market in which it competes. An outline of the decisions facing the columns group when the research project began follows this discussion.

2.2 An Overview of the Avondale Division

The Avondale Site is part of Hewlett-Packard’s Analytical Products Group (APG). APG manufactures products which aid customers in separating and identifying the different components of various types of chemical samples. Major products include the liquid chromatograph (LC), the gas chromatograph (GC), and the mass spectrometer. The Avondale Site is primarily responsible for the production of gas chromatographs and related devices, while each of the other two major products are manufactured at their own respective sites. As part of APG, the Avondale Site’s major customers include the chemical, pharmaceutical, oil and energy, medical, and food and flavor industries, as well as environmental labs and universities.
Chapter 2

Hewlett-Packard acquired the Avondale facility from F & M Scientific in the late 1950's. At that time, the plant, which had spun off from DuPont, produced gas chromatographs. Hewlett-Packard organized the plant to manufacture gas chromatographs and accessories, with R&D, marketing, and support functions located at the site as well. The plant today manufactures newer models of the gas chromatograph, automatic sampling devices, computerized chromatographic data handling systems, atomic emission detectors, and analytical capillary columns. The plant is fairly well integrated, employing a metal fabrication shop and, until very recently, a PC board assembly area. In addition, the company operates a nearby warehouse and call-in distribution center which supplies columns, sample vials, and many other analytical product accessories. Total sales for the Avondale division amounted to over $100MM in 1990.

2.3 History of the Columns Group

An analytical GC capillary column is simply a glass tube through which chemical samples are injected to be separated into their various components. The glass capillary is internally coated with a polymer specific to the type of sample to be tested. In a gas chromatograph, samples are heated to the vapor phase and forced through the column by a carrier gas such as helium. As the sample passes through the narrow column, it diffuses in and out of the polymer where its various molecules diffuse at different rates. In this way, like molecules travel through the column at equal speeds while different molecules travel quicker or slower. At the end of the column, molecules pass through the GC's detector which records the amount of molecules passing through it at a given time. Figure 2-1 presents this operation while Figure 2-2 shows an actual chromatogram.

Until 1978, analytical GC columns were made of Pyrex glass. These columns were rigid and fragile, and therefore difficult to use and to manufacture. Columns were
produced by drawing glass tubes through a guide which formed the tubes into spirals. Drawing speed was about 0.5m/min. Installation of these columns into the GC was both difficult and unpredictable, as the inflexible ends of the columns needed to be straightened by heating the glass to the softening point, compromising the polymer inside.

At the time, HP did not manufacture or market columns, but had begun to research column production in conjunction with the development of the new 5880A gas chromatograph. In experimental designs of the 5880A, engineers had problems determining what caused poor measurements. Several possibilities were related to the column itself, such as connections between the column and the injection port or detector, damage from end straightening, or poor column quality in general. Engineers at the Avondale Site began to look at new methods of manufacturing columns to offset these problems.3

During a technology meeting, HP's vice-president of R&D suggested that Avondale engineers visit HP Labs in Palo Alto, CA where researchers were investigating drawing technologies for fiber-optic applications. The Avondale engineers observed flexible fiber-optic quartz being drawn at 1m/sec, over 100 times faster than Pyrex columns, and they saw tremendous opportunities for improving column technology. The optical fiber was solid, however, not tubular as needed for columns. But the engineers noted that the solid preform from which the fiber was drawn started as a tube before being collapsed into a solid rod. HP Labs was able to draw one of these tubes into several meters of 200 μm inner-diameter tubing which was brought back to Avondale.

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Figure 2.1: Separation of sample components in a capillary column.

Figure 2.2: A sample chromatogram
Back at Avondale, the quartz tubing was coated and tested using samples that had been difficult to separate with the rigid columns. The result amazed chemists at the facility. Not only was the tubing flexible and strong enough to be tied in a knot, but the purer glass and longer columns allowed for unprecedented separation capabilities. Sensing a revolution in the science of separation technologies, Hewlett-Packard decided to manufacture and market capillary columns.

Production

HP needed to address several issues before commercializing the new columns. First, they needed to replace the coating which protected the outside of the fiber from damage which would break the tubing. The rubber coating on the optical fiber would not withstand the temperatures inside the GC oven. Engineers switched to a polyimide coating material to solve this problem, although the solvents used in the material prevented UV drying or drawing much faster than 0.1m/sec. Second, fused-silica, a purer glass which would provide greater chromatographic performance, replaced quartz as the capillary material. In addition, because column capillaries have larger diameters than the solid optical fiber and are hence less flexible, HP separated the strength proof-testing done online in fiber-optic manufacturing from the drawing process to avoid breakage during draws. If the tubing breaks during a draw, operators must reset the process and wait for the tubing to restabilize at the appropriate diameter, scrapping all tubing produced in the meantime.

Pressure to be the first-to-market with the new columns drove a rapid development of the capillary manufacturing process. Within eight months, Hewlett-Packard had developed its own drawing tower and furnace with controls. In addition, they built a clean room to house the process and developed a proof testing machine, baskets to hold the
columns, and a machine to wrap the tubing on the baskets. The manufacturing process is represented in Figures 2-3 and 2-4.

![Process Flow Diagram](image)

**Figure 2-3:** Process Flow Diagram - Column Production

The first two processes of Figure 2-3, acid etch and firepolish, were developed as a means to eliminate any surface flaws on the tubular preform prior to the preform being drawn into capillary tubing. Etching involves submerging preforms into acid for a specified amount of time to round any scratches or cracks and decrease stress concentrations. Firepolishing anneals surface defects by rotating the preform in a lathe while an OH flame travels down the preform length a number of times.

During the draw itself, three variables are controlled: preform speed, take-up speed, and furnace temperature. All three are used to control the diameter of the capillary tubing.
The first two control the inner diameter according to the following relation, assuming constant mass flow through the furnace:

\[(OD^2 - ID^2) \cdot v_p = (od^2 - id^2) \cdot v_c,\]

where \(OD\) and \(ID\) are the outer and inner diameters of the preform, respectively, \(od\) and \(id\) are the diameters of the capillary, \(v_p\) is the preform speed, and \(v_c\) is the capillary take-up speed. Given constant preform and take-up speeds, a higher furnace temperature causes the tubing to collapse to smaller diameters. With known preform diameters, a constant draw ratio \((v_c / v_p)\), and a measured capillary outer diameter, operators control the capillary inner diameter by varying the furnace temperature to obtain the outer diameter which satisfies the above equation.

As the newly-drawn capillary tubing exits the furnace, it is drawn through a coating cup containing the polyimide solution and then through a series of heating zones where the polyimide is cured. Dry tubing exits the heating zones and is spooled onto a drum. Because a thicker protective layer is required which cannot be applied without a much longer drying time, a second coat of polyimide is applied on another tower specifically designed for recoating.

After recoating, a reel of tubing is subjected to a tensile stress proof test. The entire length of tubing winds through the machine which tests for weak spots. When breaks occur, lengths of tubing too small to be made into a column are discarded. Yield loss at this step was a serious problem for HP. Tubing which passes the tensile test is wound on baskets and cut to specific column lengths. From there, the tubing is coated with the internal polymer which defines the column application, tested in a GC, packed, and shipped to the distribution warehouse.
Hewlett-Packard was the first company to introduce fused-silica capillary columns to the market, but they were quickly followed by several others. Because of the popularity and obvious advantages of the new columns, the Avondale columns group almost
immediately began to operate at the full capacity of its two-shift operation. Therefore, little time was available for experimenting with ways to optimize the drawing process. However, the columns group was profitable, and because the primary focus of the division was on the GC itself, there was no pressure to spend much effort on improving the columns business. In 1982, a new tower was added to the capillary drawing room, but it coincided with the introduction of megabore columns, a wider diameter column with applications for different separation samples. These columns, as well as the smallbore and largebore columns already in commercialization, sold well enough that the second tower was also at full capacity. Therefore, the process remained unchanged for the thirteen years since the process had been rushed into operation.

2.4 The Capillary Columns Market

The columns market has grown steadily since the introduction of fused-silica capillaries in 1978. In 1990, the market was estimated at $42M worldwide annual sales with approximately 60% of worldwide microcolumn separation applications using fused-silica capillary columns. The market has grown at almost 14% per year, and continued growth is expected given current trends in environmental testing and personal monitoring. As the customer base grows, so should the need for new polymer phases to meet new applications.4

There are currently five major competitors supplying capillary columns. Hewlett-Packard, which patented fused-silica columns, has patent licensing agreements with some of the competitors and is trying to enforce the patent with others. The market leader, not Hewlett-Packard, currently owns about 42% of the market, while HP is a distant second.

4 Ibid., p.912.
Some of the newer competitors have begun to capture market share and threaten the leaders' positions.

The columns market serves many industries, including chemicals, pharmaceuticals, medical analysis, and environmental testing. These customers, through market surveys, cited column quality as the most important reason for choosing a capillary column supplier. Technical support and product selection also strongly influenced customer buying decisions. Price was not considered an important factor in column selection. Most customers designate peak resolution as the most important column quality measure. Peak resolution, the distinct separation between peaks in chromatograms such as the one shown in Figure 2-2, allows customers to more accurately determine the quantity of certain sample components. Another important characteristic is column-to-column reproducibility which enables customers to replace like columns and obtain consistent measurements without recalibrating the GC. Customers also desire column inertness, which prevents samples from reacting with the column to give false measurements, and "low bleed", the resistance of the column's polymers to breaking down and obscuring readings at high temperatures.

Hewlett-Packard maintains an image as a quality supplier of capillary columns. HP's "Ultra-Performance" columns offer customers the best reproducibility and tightest performance specifications of any column in the industry. HP's strength also comes from the company's installed base of GCs worldwide and the reputation of the Hewlett-Packard name as a reliable corporation. However, HP lags its competitors in several areas. The biggest weakness is a narrow product line. HP does not supply columns for many applications, which causes them to lose not only customers who desire those specific applications, but customers who need a range of applications and would rather purchase from one supplier. Hewlett-Packard columns also have unique diameters, different from
the industry standards established by the rest of its competitors. Customers who might switch to HP columns would need to calibrate their GCs and reprogram their test procedures to compensate. Running at full capacity has also hurt HP in the market place by making them less flexible to meet changes in demand. It is crucial for suppliers to keep columns "on-the-shelf" for immediate delivery. HP has at times suffered from low column availability, a critical customer service measure, and lost potential sales to competitors who could promise customers quicker delivery. Finally, Hewlett-Packard sells columns through a single distribution site, Hewlett-Packard Analytical Direct (HPAD), which takes customer orders through a call-in service. Customers are not actively contacted and until recently, columns sales were not managed separately from the rest of the analytical supplies which include such products as computer paper and plotter pens. HP's competitors, on the other hand, have wide distribution networks to market their columns and support existing customers.

Unlike many of its column competitors, HP draws its own capillary tubing. The market leader, for example, purchases spools of tubing from a capillary supplier, wraps it on baskets, and internally coaxes it for the necessary column application. In previous years, HP perceived their capillary drawing capabilities as a competitive advantage. Column competitors had cited problems with weak or active tubing purchased on the outside. Tubing suppliers, who produce mostly optical fiber, did not understand the chromatographic qualities needed in the fused-silica capillaries, while HP had spun its columns group out of GC manufacturing. Recently, however, suppliers had improved their quality to the point where HP began considering supplementing its own tubing capacity with tubing from outside suppliers.
2.5 Columns Group Business Strategy

Shortly before this research project began, Hewlett-Packard evaluated its position in the columns market and decided that industry profits and market growth warranted refocusing the columns group to capture a larger share of the market. As part of the plan to accomplish this transformation, HP assigned a project manager to columns at HPAD. In addition, management decided that HP would attempt to grow by targeting HP GC customers who did not currently purchase HP columns, introducing new columns to broaden the product line, and investing in polymer R & D to achieve separation technology breakthroughs. Through these initiatives and in light of market trends, HP estimated volume growth of about 20% per year.

While management agreed that the columns market was worth a new commitment, they were aware that such a strategy would require several changes in the columns group's current operations. First came the need for talented engineers to research current technology in columns manufacturing and to make necessary improvements to the capillary drawing, coating, and polymer synthesis processes, to name a few. Second, of more obvious and immediate concern, was the need to increase the present drawing capacity. The capillary lab had been operating at full two-shift capacity for some time, and significant overtime had been necessary to keep the columns backlog from growing too large. HP faced the following decisions on how to increase the drawing capacity:

1) Add a third shift
2) Build another capillary-specific drawing tower
3) Purchase and adapt a state-of-the-art fiber-optic drawing tower for capillary drawing
4) Purchase tubing from an outside supplier
Before this research project began, HP was trying to evaluate which of the four options alone or in combination would best meet their needs.

HP's first option to increase capacity was to add a third shift. Doing so could increase the capillary drawing capacity by about 40%. However, this was an expensive option, given that two additional operators would be needed to man the two towers, whereas a third tower in the lab could probably be handled by the two operators. Furthermore, no other department in the plant operated around the clock, so that the third shift operators would be alone if any emergency occurred. Finally, a third shift would only offer a temporary cushion. With two shifts plus overtime, the lab could barely keep up with the present demand. If column volume grew according to the new business strategy, the lab would reach full capacity again in a little over a year.

Building a new drawing tower would give the same initial boost as the third shift. HP felt in building a new tower that successful modifications to the original tower design might enable the engineers to improve the functions of the original towers. With the third tower, engineers could also temporarily take one tower off line for experimentation without cutting into production as badly as if taking one of two towers from a three shift operation. However, building a new tower would also involve a substantial investment of both time and money (~$350K), and the added capacity would need to be supplemented in a year or so with a third shift or another tower.

Buying and adapting a new fiber optic tower offered similar benefits to building a tower but with some advantages. Although this tower would require some adaptations in order to manufacture capillaries, buying a tower would not require nearly as much time of HP personnel. Facilities were already quite busy managing the plant's relocation to a brand new building. In addition, a modern tower included equipment that would allow for
unattended operation and faster drawing speeds, therefore providing more drawing capacity than the older design. Buying a new tower required the largest one-time investment of the four options, estimated at about $500K.

The last option was to purchase capillary tubing from an outside vendor. If this vendor's product proved reliable, HP would consider leaving the capillary drawing business and focusing on polymer technology. Early in the project, we evaluated a major supplier's megabore tubing, requested price quotes for the different tubing sizes, and obtained samples of their megabore capillaries. The sample of the tubing, which in the past had a reputation for poor quality, was actually of better quality than the megabore drawn by HP. Strength tests showed that the vendor's megabore was virtually flawless, and would achieve much higher yields through the tensile tester than did the HP megabore. The vendor's megabore tubing would also cost less than HP's internal costs to produce it. However, Hewlett-Packard had several concerns about divesting their drawing capabilities.

2.6 HP Vertical Integration Strategy and Concerns

In evaluating the option of leaving the capillary drawing business, Hewlett-Packard needed to consider several factors:

Cost - There is much debate over the relative cost advantages and disadvantages of vertical integration. On one hand, companies that integrate backwards into the supply chain, like HP into raw capillaries, can reduce costs by absorbing a supplier's profit margins. If a non-integrated company's supplier faces little competition or if there are significant switching costs for changing suppliers, the supplier can raise prices leaving the company with little alternative but to pay. In addition, integrating backwards avoids the intermediate

5These tests will be described in Chapter Four.
Chapter 2

taxes and purchasing overhead associated with buying products or services from outside of
the company. On the other hand, a supplier may have expertise or economies of scale that
a company could not easily duplicate if the company were manufacturing the product in
house. The demand or capacity of downstream operations may also not fit well with the
upstream process, causing inefficient utilization or poor inventory management. These
inefficiencies can lead to costs higher than a company would suffer if subcontracting the
upstream operations.

The capillary vendor quoted prices for the diameters of tubing used by HP, and
while the prices for the smaller diameters were slightly higher than HP’s internal costs
(fully-loaded with overhead), it would cost about 7% less to buy and use the vendor’s
megabore than it did to make it. And because the vendor claimed to have enough capacity
to supply HP’s needs, HP could avoid the investments required for a new tower or a third
shift. However, because there were very few capillary vendors who could support HP’s
capillary demand, this vendor could raise prices when HP dismantled its drawing
operations, becoming dependent on a single supplier.

*Quality* - Some argue that backward integration provides a company with greater control
over product performance and quality because of better information and communication.
Others propose that because of biases or company politics, quality measurement becomes
less objective, possibly leading to poorer quality than a supplier fighting for business
would produce.

We tested samples of the capillary vendor’s megabore to be stronger and just as
inert as HP’s own product. However, could HP trust that this vendor had indeed
conquered its previous quality problems and that the samples provided to HP (2 months
late, no less) were indicative of the average product? What influence could HP exert over
the supplier to insure that they maintained and improved quality? Could such influence bring about quality improvements that HP could not demand from its own operations for twelve years?

Delivery and inventory management - Some argue that delivery and schedules, as an issue of communication and coordination, can be better handled within a company that shares common goals, training, information systems, and facilities. Others argue that particular operations can have their own subcultures with specialists more concerned with the group's own agenda than with the company's needs. Therefore, a company gains little in coordination through backward integration.

Hewlett-Packard's capillary operation is integrated with the rest of columns manufacturing, with all employees reporting to the same supervisors and manager, so there are no separate subcultures. With its own capillary lab, Hewlett-Packard can set a daily schedule to meet the changing demand for all of its diameters. This demand is quite unpredictable, often requiring several days dedicated to drawing one diameter only. If HP relied on a single vendor who would not make deliveries "Just-In Time", it would need to buy large quantities of tubing at a time, constantly expedite deliveries from the vendor, or figure a way to smooth the tubing flow. In addition, the potential vendor is located in the western part of the country, making communication and quick response to emergency demand very difficult. In general, coordination and communication can be handled effectively with an outside supplier. However, long distances, different time zones, and contrasting company goals and cultures all combine to make this coordination more difficult.

Risk - If there are a small number of suppliers or significant switching costs, a company which vertically integrates can isolate itself from the financial difficulties or unforeseen
problems like strikes which may obstruct a supplier’s ability to maintain steady deliveries and service. The buyer cannot easily influence some supplier problems, for example labor disputes. On the other hand, backward integration requires an investment that may limit a manufacturer’s flexibility. This suggests that those companies focusing on process and technological flexibility may be better off relying on short-term supplier relationships. For instance, if a new technology obsoletes the upstream operation, a vertically integrated company may find itself saddled with outdated processes or equipment. In relation to this risk, a suggested test of whether or not to vertically integrate is to ask whether the downstream company would be willing to commit to a ten-year contract with a single supplier.\(^6\)

In evaluating the particular capillary vendor, we found that the vendor was not financially sound. During the project, this privately-owned company was put up for sale, partly because the owners wanted to part ways and take their respective shares of the investment. HP was obviously concerned with the long-term viability of such a supplier. In addition, if the company were bought by a columns competitor, HP could find itself shut off from its capillary supply or subjected to high prices and second-rate quality. There was always the possibility of finding another vendor, but not only were capillary vendors scarce, several of them had begun to stop selling capillaries because of low margins compared to optical fiber.

*R&D Capabilities* - By integrating backward, a company can keep control over its proprietary processes and technology. Through R&D efforts, a company might realize innovations that provide a substantial competitive advantage. However, with internal

production, it may miss out on innovations developed outside of the company or be too inflexible to take advantage of new technologies.

Leaving the capillary business meant losing the ability to research capillary and other separation technology. Although the GC drove the Avondale Site, columns had played a role in developing advanced models of the GC. The invention of the fused-silica capillary column solved many of the development problems on the 5880A GC, and the introduction of megabore tubing provided for sample injection directly onto the column in the present 5890 model and associated automatic sampling equipment. A similar breakthrough could lead to ovenless GC's, electromagnetic separation, or columns on a silicon chip. HP had to consider the danger of divesting from such capillary research because, as Hayes and Wheelwright state, "the opportunities and threats stemming from technological change typically originate from material and component innovations that start far back in supply channels."\(^7\)

The HP management team, however, was not in agreement as to the strategic advantage of capillary drawing. While some felt it important to continue research in capillary technology, others believed that time and money would be better spent on polymer research and other GC-related innovations. If capillary vendors maintained their operations, perhaps it would be wiser to entrust R&D efforts to an organization that was committed to glass science. Because columns was somewhat regarded as a secondary business at Avondale, HP might be and in fact had been reluctant to invest the resources necessary to keep its capillary technology ahead of the competition. A dedicated capillary supplier could not afford to ignore its primary business in this way.

\(^7\) Ibid., p.284.
Overall, there is no simple answer as to whether or not to vertically integrate, in which direction, or to what degree. For this reason, the issue has received much attention in industrial and business literature. Through the research at Hewlett-Packard, we feel that it is wise for the columns business to remain vertically integrated into capillary drawing, although there are several tradeoffs as discussed above. The primary reasons are to maintain R&D capabilities and to protect existing and potential technology, and to avoid reliance on a very small supplier base which is judged to be unstable.

2.7 Process Improvement Option

Until now, we have discussed Hewlett-Packard's options for increasing fused-silica capillary capacity and addressing strategic needs through adding human resources, investing in additional capital equipment, and buying capillary tubing from an outside vendor. All of these options have been considered and weighed given that HP's present processes remain unchanged. However, would these options change if Hewlett-Packard could somehow alter the drawing process? Low yields through the tensile tester suggested that the process may have had room for improvement. How would such changes affect capacity, costs, and quality, and what investments would be required to achieve these results? If Hewlett-Packard were to answer these questions, would the process changes need to be actually implemented and measured? HP did not want to invest the time and equipment to repeatedly change the process if such changes did not address HP's needs. What HP needed was a way to predict the effect of such process changes not only on the quality of the capillary tubing, but on the strategic position of the columns group. In this way, the operational and strategic needs could dictate in which manner the process should be changed while at the same time, such process changes could alter the strategic situation that was forcing Hewlett-Packard to choose between the options previously discussed.
2.8 Summary

This chapter provided an overview of Hewlett-Packard's Avondale Site and in particular the GC capillary columns business group. It described the invention of fused-silica capillary columns, including HP's commercialization of columns and a discussion of the capillary columns manufacturing process. Capillary columns became an immediate success, but strong demand and limited production capacity prevented HP from optimizing the capillary drawing process. The chapter then focused on the columns market today, HP's strengths and weaknesses within the market, and HP's subsequent strategy for increasing its strength within the market.

Given the Avondale columns strategy, HP considered several options for increasing drawing capacity and meeting its long-term growth and strategic needs. The chapter discussed the benefits and weaknesses of these options, and detailed HP's concerns with divesting from capillary drawing altogether. Finally, this chapter suggested that HP also had the option of addressing its needs through improving the drawing process. To test the feasibility of this option without actually implementing and measuring the effect of process changes, HP needed a model which could predict the overall strategic operational implications of proposed changes. The chapter thus provided a foundation for understanding the need for and benefits of the integrative parameter selection model to be developed in the next two chapters.
Chapter Three
Toward Dynamic Control -
The Predictive Process Model

3.1 Introduction

In the book, Dynamic Manufacturing, the authors describe four degrees of process control. Under the first degree, reactive control, one must identify critical output parameters and measure them to determine whether the product is good or bad. Targets and tolerances for critical output variables are set and monitored. Upon achieving reactive control, one can recognize when a process varies outside of normal or acceptable tolerances and initiate corrective actions.

The second degree of control is preventive control. A process is under preventive control when one identifies sources of abnormal variation and understands the directions of cause and effect relationships. By controlling these sources, one can prevent abnormal variation.

A process is said to be under progressive control if the relative strengths as well as directions of cause and effect relationships are defined and controlled. Second- and third-order interactions and more subtle sources of variance are understood. Under progressive control, the process parameters can be used to predict the performance of the process and tighten the distribution of the output performance measurements.

---

Finally, *dynamic control* incorporates other objectives such as profit or new product opportunities into the process model. Under dynamic control, one can simulate the effect of changes in process parameters on the full-system and control them accordingly.

This chapter discusses the efforts to bring the capillary drawing process under progressive control. This will be done by presenting the experimental methods and tools used and the design of the experiments themselves. Alternative approaches to modelling the process are applied and tested, and a predictive model is developed. Validation tests of the various regression models are included in the appendices. Chapter Four extends these results to the integrative model and dynamic control.

### 3.2 Design of Experiment

To some extent, the drawing process had been operating under reactive control for years. Operators tested the strength of the capillaries, monitored critical diameters, and collected and tabulated yield data. When capillary diameters began to vary significantly during draws or when yields began to drop sharply, operators called in maintenance to replace furnace elements, to adjust preform or take-up motors, or to change pinch belts. Usually, these actions were enough to bring the process back to normal operations. However, yields as low as seventy percent for megabore tubing were considered normal. Until this project, nobody had ever attempted to identify and to isolate the effects of certain drawing process parameters on specific capillary characteristics. Understanding and controlling these factors would move the drawing process toward preventive control.

In order to achieve preventive control, we designed an experiment through which we could utilize two different process optimization methods. We based the actual layout of the experiment upon Dr. Genichi Taguchi's Robust Design method. (For a detailed discussion of this method, the reader is referred to *Quality Engineering Using Robust*...
Design by Madhav Phadke. The second method, to be discussed later, used some of the same data generated by the Taguchi experiments.

3.2.1 Overview of Taguchi Robust Design Method

The Taguchi method focuses on decreasing the "total loss to society due to functional variation and harmful side effects". This method relates loss to society to certain costs rising from variability in product performance. Thus, engineers who follow Taguchi's methods seek to control processes in a way that minimizes process variance as well as optimizes the mean performance response, whereas most other methods focus solely on the mean performance. Unfortunately, these two outcomes are often independent or negatively-correlated and engineers must trade off between mean and variance.

The first basic tool of Robust Design, the signal-to-noise ratio, helps engineers to balance the tradeoff between mean and variance and determine the best overall response. The robust design method employs signal-to-noise ratios as a measure of quality. For a "nominal is best" problem, the signal-to-noise ratio expressed in decibels is:

\[
\text{Signal-to-noise ratio (SNR)} = \eta = 10 \log_{10} \left( \mu^2 / \sigma^2 \right)
\]

where \( \mu \) is that desired portion of the response controlled by process settings and \( \sigma \) represents the effect of variance. Maximizing the SNR is equivalent to minimizing the quality loss and to minimizing sensitivity to noise factors.

The second major tool used in Robust Design is the orthogonal array. The orthogonal array allows for the effects of several parameters to be determined simultaneously in a series of experimental trials. The array specifies common testing

9 M.S. Phadke, Quality Engineering Using Robust Design. AT&T Bell Laboratories, 1989.
10 Ibid., p. 4.
conditions for comparing several combinations of process parameter settings in a way that enables experimenters to estimate individual parameter effects independently of others. By constructing the correct array for an experiment, one can derive valid conclusions about the experimental factors while performing a fraction of the experimental trials necessary to test the factors individually.

The first step in constructing an orthogonal array is to determine the number of experimental factors to be analyzed and the number of different levels or settings of each factor to be used during the experiments. For example, for a coffee-making experiment, one may select bean quantity as an experimental factor and would try one-half, one, and two tablespoons as the three factor levels. An array is then constructed in which the rows represent the experimental trials and the columns represent the experimental factors. The array is said to be orthogonal when for each pair of columns, all combinations of levels occur, and they occur in experimental trials an equal number of times. Figure 3-1 shows an orthogonal array for our coffee-making experiment with three factors at three levels each. This experiment would coincide with using columns 1, 2, and 3 in the standard L9 \((3^4)\) array while leaving the fourth column empty. The name of the array signifies the number of rows and columns it has. Thus the L9 \((3^4)\) array has nine rows and four three-level design parameters. (For a listing of standard arrays, the reader is referred to Phadke, Appendix C)

In addition to the experimental factor or process design factor array, Robust Design calls for construction of another array for controllable noise factors. This array, sometimes called the outer array, is constructed the same way as the control factor array. Experimental trials defined in the design factor array are repeated for every noise combination defined by the outer array. In this way, experimenters can determine the sensitivity of a response to
noise factors and calculate a signal-to-noise ratio. In the coffee-making process, for example, we might select the filter brand as a noise factor, and test three different brands as three noise levels. By combining the two arrays, we would use the matrix of Figure 3-2...
for our Robust Design experiments. Experiment 1a in Figure 3-2 would be performed using the first process parameter combination and a Brand A filter, while experiment 3b would be done under the conditions of the third parameter combination and a Brand B filter.

3.2.2 Overview of the Alkhairy Method

In order to try an alternative to Taguchi’s Robust Design method, we analyzed the experimental data according to a newly-proposed method. Dr. Ashraf Alkhairy has developed a method for product and process optimization.\textsuperscript{11} Like Robust Design, the Alkhairy method relies on orthogonal arrays for factor analysis, and looks at the effect of noise factors on the process response. However, the Alkhairy method is different from Taguchi’s method in two areas as applicable to this project: 1) the use of signal-to-noise ratios, and 2) the treatment of noise factors.

Taguchi uses signal-to-noise ratios as the exclusive quality measure, and from them determines the optimum combination of factor levels which maximizes the SNR of the overall response. Such an analysis is very valuable when one seeks preventive control over a process; that is, an understanding of the direction of cause-and-effect relationships. In order to achieve progressive control, however, one needs to determine the relative strengths of first-order factor effects and the effect of two- or three-factor interactions. For our study, it was critical that we achieve such control and a predictive model for the drawing process. Alkhairy argues that the SNR is not always the best transformation for performing the regression analysis necessary for model formulation. In addition, the Alkhairy method involves testing for higher-level interactions which may be significant and

could be missed using Taguchi’s method. Thus, the Alkhairy method calls for performing regression on several transformations of the measured response. By examining the standard errors and applying model validation tests such as residual analysis to the regression models, experimenters can determine the transformation from which the most accurate model can be produced.

The Alkhairy method also treats noise factors differently than does Robust Design. We recall that in the Robust Design method, noise factor combinations for the experiment are defined in a separate outer array and that each design factor combination is repeated for each noise factor combination. In the coffee-making example of Figure 3-2, we would actually perform 27 experimental trials. The Alkhairy method, however, does not treat noise factors explicitly. Instead, noise factors are treated like design factors and included in the design factor array, which substantially reduces the number of experiments. Placing noise factors in unused columns of the orthogonal array does not disturb the orthogonality, so that one can determine the effect of noise factors in the same way as for the design factors. However, to avoid masking or confounding the effects of design factor interactions, noise factors should occupy columns that do not coincide with anticipated strong design factor interactions.

Figure 3-3 shows a possible matrix for our coffee-making experiment using the Alkhairy method. The noise factor "filter brand" has been modelled as a design parameter, occupying the fourth column of the L9 array. The outer array from the Robust Design matrix of Figure 3-2 has been included to show the way in which the Alkhairy method reduces the number of experiments. The combination of levels specified in the four-column design factor array are represented by the highlighted experiments in the original
Robust Design matrix. The Alkhaairy method, while still capturing the effects of the noise factor "filter brand", would require only these 9 experiments for analysis.

<table>
<thead>
<tr>
<th>Experiment No.</th>
<th>Beans (Tbslnps)</th>
<th>Cream (oz.)</th>
<th>Sugar (lumps)</th>
<th>Noise Factor</th>
<th>(Filter Brand)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5</td>
<td>1</td>
<td>1</td>
<td>A</td>
<td>1A</td>
</tr>
<tr>
<td>2</td>
<td>0.5</td>
<td>1.5</td>
<td>2</td>
<td>B</td>
<td>2B</td>
</tr>
<tr>
<td>3</td>
<td>0.5</td>
<td>2</td>
<td>3</td>
<td>C</td>
<td>3C</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>C</td>
<td>4C</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>1.5</td>
<td>3</td>
<td>A</td>
<td>5A</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>B</td>
<td>6B</td>
</tr>
<tr>
<td>7</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>B</td>
<td>7B</td>
</tr>
<tr>
<td>8</td>
<td>2</td>
<td>1.5</td>
<td>1</td>
<td>C</td>
<td>8C</td>
</tr>
<tr>
<td>9</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>A</td>
<td>9A</td>
</tr>
</tbody>
</table>

**Figure 3-3:** Alkhaairy method array for a coffee-making experiment. Only the designated experimental trials would be performed.

3.3 The Capillary Drawing Experiment

In order to develop a predictive model for the capillary drawing process, we needed to bring the process under progressive control. At the same time, we wished to test the application of Alkhaairy's method in an actual production environment. Specifically, we set out to compare the Alkhaairy method to the Taguchi Robust Design method by using each to analyze and optimize the drawing process. The following sections describe the process of designing the experiments which we performed over the course of this research project.

3.3.1 Selecting Response Variables

3.3.1.1 Selecting Desired Characteristics

The first step in designing an experiment is to identify those outputs which are to be measured. In order to optimize the process, one must first know what kind of process
response is desirable, what kind is not, and how to tell the difference. By measuring the response of the process and determining the effect of process settings on that response, one can select the combination of process settings which produces the most desirable response. The responses selected for our experiments were 1) capillary strength, and 2) tubing inertness.

Capillary strength was deemed important for several reasons. First, stronger fiber would lead to higher yields through the tensile tester. Low test yields were a problem particularly on megabore tubing, where up to thirty percent of all tubing drawn was scrapped prior to any downstream processing. These low yields were manifest in high manufacturing costs and limited drawing capacity. Second, tubing which survived the tensile test sometimes broke in downstream operations where more value-added costs were incurred. Worse yet, weak tubing could break in a shipping box or in a customer's GC, damaging the reputation of HP and its products. Finally, the average tubing length between breaks would increase as the tubing strength increased. Thus by increasing the strength, HP might be able to market longer columns such as the 60m megabore already supplied by HP's competitors.

The benefits of increasing the inertness of the capillary tubing were less obvious. It was generally accepted that less active tubing would be less liable to distort chromatograms by reacting with components of the sample. In fact, when fused-silica was first used as a substitute for Pyrex and quartz in capillary columns, chromatographers were able to separate components with far greater resolution than they had ever experienced previously.12 We felt that increasing the inertness of the fused-silica might lead to even better separation resolution and to a new line of columns for specialty samples. At the

least, we hoped that by reducing the variability of tubing inertness, we could improve the column-to-column reproducibility so highly valued by the customers.

We did not know, however, if further deactivating the tubing would have much of an effect at all. With short Pyrex columns, the activity of the glass influenced and detracted from column performance. With fused-silica however, we were unsure whether the glass was so inert that column performance was determined solely by the polymer coating. If this were the case, we would concern ourselves with tubing strength only and optimize the process accordingly. While the drawing experiment would be used to determine the effect of drawing process parameters on tubing inertness, we tested the influence of fused-silica inertness on column performance with another experiment.\textsuperscript{13}

\subsection*{3.3.1.2 Selecting Measurements}

The two process responses were measured in the following way:

\textit{Strength}:

For each experimental trial, approximately 125 meters of tubing were drawn. For each trial approximately thirty 2.5-meter samples were stretched until breaking using an Instron force-measuring machine. The breaking force for each sample in Newtons was then converted to breaking stress by the following relation:

$$\sigma = 1000 \times \frac{F}{A},$$

where \(\sigma\) is the breaking stress in Newtons, \(F\) is the breaking force in Newtons, and \(A\) is the cross-sectional area of the tubing in square millimeters. All of the sample breaking stresses were recorded and plotted on a normal probability plot such as the one shown in Figure 3-4. In Figure 3-4, one notices that the sample distribution flattens to a roughly

\textsuperscript{13} This experiment, discussed later in the chapter, showed little correlation between tubing inertness and column performance.
vertical line at about 5 - 5.5 GPa. Points which fall on this line are free of defects which weaken the tubing, and the line represents the maximum stress which flawless tubing can endure before fracturing.

Points not on the vertical line represent samples which contain some degree of defects. These points typically extend linearly in the normal probability plot from the "bend" in the vertical line toward the bottom left corner of the plot. In Figure 3-4, we see that this "line" crosses 2 GPa at about 20%. This signifies that approximately 20% of the samples would fracture if subjected to a stress of 2 GPa. We will use this information later in Chapter Four.

The quality measure for each experimental trial was derived from the normal probability plots. This quality measure was defined as:

\[
\text{Quality response} = \sin^{-1} \left( \frac{\text{# good}}{\text{total}} \right)^{1/2},
\]

where "# good" represents the number of breaks which occurred at the theoretical stress limit (vertical line) for fused-silica and "total" is the total number of samples for the trial. The arcsine square root transformation stabilizes the variance, making the variance at low and high ratios roughly constant. Without this transformation, variance at low ratios would be overstated. (i.e. Variance between 3/30 and 2/30 would be interpreted to be more significant than between 28/30 and 27/30.)

**Inertness:**
To test inertness, we measured the retention index of the experimental tubing using a fixed chemical sample.\(^{14}\) This measure was obtained by first measuring the retention index of a coated megabore column. We then connected a segment of the uncoated experimental

\(^{14}\) The retention index is a measure of the duration a specific test component in a chemical sample remains inside the column relative to other components.
tubing in series with the column and measured the retention index of the combination. Active experimental tubing would increase the retention index more than inert tubing. We used the incremental increase in the retention index as the inertness measure, with zero the best possible measurement.

![Normal Probability Plot](image)

**Figure 3-4:** Normal probability plot of sample breaking stresses for an experimental trial
3.3.2 Selecting Process Parameters

With response variables selected, the next step was to select the process parameters whose effects we wished to test and control. After a thorough investigation of the process, we identified several parameters which could have had some effect on the response variables. These parameters were as follows:

- Preform size
- Preform vendor
- Acid etch time
- Acid etch concentration
- Firepolish time
- Furnace temperature
- Drawing speed
- Capillary wall thickness

Figure 3-5 shows these factors in relation to the capillary manufacturing process. Note that five of the eight process parameters identified for testing relate to processing the preform prior to capillary drawing. Later discussions will show how this situation affected the final experimental design.

![Diagram](image)

**Figure 3-5:** Process parameters for the capillary drawing experiment.

As to their direct effect on the response variables, the above parameters were identified for the following reasons:

*Preform size* - Defects responsible for the loss of glass strength are on the glass surface. By varying the cross-sectional area of the preform, we might influence the strength of the
capillary tubing by spreading preform defects over different lengths of capillary tubing. In other words, a preform with the same outer diameter but a smaller inner diameter than another preform has a smaller overall surface area but will yield more tubing.

*Preform vendor* - Although difficult to detect, different vendors might supply preforms that were relatively more or less flawed, pure, or variable. All of these factors could influence strength and inertness.

*Acid etch time and acid concentration* - Etching relieves stress concentrations by rounding cracks and scratches in the preform surface. Varying both of these parameters would alter the effectiveness of etching on tubing strength. There were also questions as to whether the acid reduced the purity of the fused-silica, increasing activity.

*Firepolish time* - Firepolishing of the preform had been accepted as one of the best ways to strengthen glass.\(^{15}\) As the preform sizes and vendors varied, more or less annealing might have been necessary.

*Furnace temperature* - Drawing tubing through a hotter furnace might anneal any surface flaws that were not eliminated during etching or firepolishing. In fact, a hotter drawing furnace might make those prior process steps unnecessary for strengthening the tubing. A hotter furnace could also drive off water or impurities trapped in the preform and produce more inert tubing.

*Drawing speed* - Varying the time that any segment of tubing spent in the furnace could have the same effect on both response variables that varying the furnace temperature would have. The temperature-time gradient could also serve to weaken the tubing if it cooled too quickly.

**Capillary wall thickness** - As with preform thickness, varying the tubing wall thickness would vary the degree to which preform surface defects were spread over the capillary tubing. A thinner wall would also reduce the stress on the tubing when it is wrapped on a basket.

### 3.3.3 Selecting Noise Parameters

The next step in the process optimization was to identify noise variables. The variables selected were to represent those parameters which 1) might influence the response variables, 2) would be difficult or expensive to control or design out of the process, and 3) could be measured and, if possible, controlled during the experimental trials. The noise variables selected were:

- Drawing tower operator
- Location on preform
- Ambient temperature
- Ambient humidity

The operator variable was selected because some operators achieved consistently higher yields than others, and all operators would continue to draw tubing. The preform location from which a segment of tubing was drawn was also thought to have some effect on both response variables because of where preform defects might be concentrated and the different lengths of time that each end of the preform spent on the drawing tower. Ambient temperature and humidity could not be controlled in the experiment, but were worth measuring. Ambient temperature would affect the gradient on either side of the furnace while high humidity might weaken or cause active sites on the preform while it sat on the tower.
3.4 The Experimental Matrix

Once the response, design, and noise variables had been selected, we began to develop the orthogonal arrays which would define the various combinations and experimental trials. At the same time, we began to examine our constraints so that we could most effectively use the time and resources available to characterize the drawing process. Unfortunately, these constraints forced us to make some sacrifices in the experimental design. We were forced to make decisions such as which design variables were most important to test, which could be easily tested, and which levels could be used.

3.4.1 Sacrifices in Experimental Design

The biggest constraint we faced was time. To draw, process, and test one section of tubing for an experimental trial took almost a full day. Because the capillary lab was already operating at almost full capacity, we could not tie up too much machine time for experimental purposes. In addition, we needed to complete the experiments within approximately five months so that analysis could be completed within the project window. Another constraint was capital. To dedicate an entire preform to one experimental trial was simply too expensive. These constraints required the following sacrifices:

*Elimination of some design parameters* - Finding and contracting new suppliers could take several months. As a result, we had to eliminate preform vendors as an experimental design variable. In addition, varying the acid etch concentration would have required some additional equipment and the development of new procedures. We therefore dropped acid concentration from the experiment as well.

*Two-level restrictions* - In order to test the remaining six process factors with more than two levels and to also estimate several interactions, we would have had to use the standard
L27 (3^{13}) array. To repeat these combinations across an outer array of four noise combinations\textsuperscript{16} for the Taguchi method would have required 108 trials, which was too many. Restricting the design factors to two levels allowed us to use the L\textsubscript{16} (2^{15}) array for 64 trials.

\textit{Blocking on the preform variables} - Because we only needed about 125 meters of tubing for each trial and had to conserve preforms, we decided to run two trials on every thin preform and four on each thick one. While we could vary the furnace temperature, draw speed, and capillary wall thickness during a preform draw, we could not vary the preform thickness, the etch time, or the firepolish time. Therefore, the latter three variables had to be placed in columns one through three in the L\textsubscript{16} (2^{15}) array. In other words, because these three factors could not be varied during the four trials of a thick preform, they really made up an L\textsubscript{4} (2^{3}) array where each of the four trials "blocked" four trials in the L\textsubscript{16} (2^{15}) array. The main effect of each of these factors would then be confounded with the interaction of the other two.

\textit{Megabore only} - Although we intended to use the experiment to increase the strength and inertness of tubing of each diameter, we did not have the time to perform experiments with all products. We decided to base all of the experiments on megabore tubing primarily because megabore strength yields were far lower than for the other sizes. With more room for improvement, it would be easier to determine the effects of the design variables because of the larger range of values possible for the response variables.

\textsuperscript{16}An orthogonal array for the two controllable noise factors, operator and preform location, at two levels each required an L\textsubscript{4} (2^{3}) matrix.
3.4.2 Selecting Levels

Because the process control factors were restricted to two levels, we could not use the standard process level as a reference point and test both a lower and higher level. We could have dropped the standard process level from the experiment and tested a high and low level. We instead kept the standard process level of each control factor as one test level and selected a second level which, if having a better effect on the response variable than the standard, would benefit some other aspect of the drawing process. For example, we chose zero minutes as a level for acid etch so that we might eliminate the use of hazardous chemicals from the process if doing so did not adversely affect the response variables. We kept the standard levels in the experiment so that we could verify with close-to-standard level combinations that the experimental measurements were within reasonable agreement with historical data.

The levels chosen for process parameters and noise factors are shown in Table 3-1.

The final experimental design is shown in the matrix of Figure 3-6.

<table>
<thead>
<tr>
<th>Process Design Parameters</th>
<th>LEVEL</th>
<th>LEVEL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>low</td>
<td>high</td>
</tr>
<tr>
<td>Acid Etch Time</td>
<td>None</td>
<td>Standard</td>
</tr>
<tr>
<td>Firepolish Time</td>
<td>None</td>
<td>Standard</td>
</tr>
<tr>
<td>Preform Size</td>
<td>Standard</td>
<td>2.5X Standard</td>
</tr>
<tr>
<td>Furnace Temperature</td>
<td>Standard</td>
<td>Standard + 1500°C</td>
</tr>
<tr>
<td>Draw Speed</td>
<td>67% Standard</td>
<td>Standard</td>
</tr>
<tr>
<td>Tubing Wall Thickness</td>
<td>67% Standard</td>
<td>Standard</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Noise Factors</th>
<th>low</th>
<th>high</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>low</td>
<td>high</td>
</tr>
<tr>
<td>Preform Location</td>
<td>First 1/2</td>
<td>Second 1/2</td>
</tr>
<tr>
<td>Draw Operator</td>
<td>Mike</td>
<td>Chip</td>
</tr>
</tbody>
</table>

Table 3-1: Experimental factors and levels for the capillary drawing experiment.
## Chapter 3

**Figure 3.6:** Robust Experimental Matrix and Results for the...
3.5 Experimental Outcomes

3.5.1 Achieving Preventive Control

Recall that a process is said to be under preventive control when the critical process parameters are identified and the direction of cause and effect relationships between these parameters and the process response is understood. Once we had completed all of the experiments in the Robust Design matrix and performed the strength and inertness tests, we analyzed the data according to both the Taguchi and Alkhairy methods. In each case, we were able to identify the most important process design factors and the levels of each which would optimize the response variables. Had we stopped our analysis at this point, drawing operators and engineers would have achieved a better understanding of how certain process parameters influence the response variables. They could then monitor and control these parameters during draws to prevent the tubing strength and inertness from varying outside of acceptable limits.

Although the experiments helped to determine the effect of the process parameters on both strength and inertness, subsequent experiments have shown little correlation between tubing inertness and column performance, at least within the inertness variance range of our experimental samples. For this reason and to simplify the following discussions, we will focus on tubing strength alone when analyzing the experimental data. The following sections detail the two methods by which we were able to optimize tubing strength.

3.5.1.1 Results from Taguchi Robust Design

The 64 experimental trials were drawn and tested as randomly as possible given the preform blocking restriction. The strength response measurements for each trial fill the matrix shown in Figure 3-6. (For example, the measurement "48.83" in the top left cell is
the strength response measurement for the experiment which used the first design parameter combination and the low level of each noise factor.) Figure 3-6 also shows the signal-to-noise ratio calculated for each of the sixteen process parameter combinations. Because the strength response variable is a "larger-the-better" variable (i.e. we want to maximize the measure), these SNRs were calculated as follows:

\[
\text{SNR} = -10 \cdot \log_{10} \left( \frac{1}{n} \cdot \sum \left( \frac{1}{y^2} \right) \right) \quad \text{(For row 1)}
\]

\[
= -10 \cdot \log_{10} \left( \frac{1}{4} \cdot \left( \frac{1}{48.83^2} + \frac{1}{45^2} + \frac{1}{60^2} + \frac{1}{50.77^2} \right) \right)
\]

\[
= 34.04
\]

The average SNR for each level of each process design parameter was then calculated so that we could determine how each parameter affects the overall strength SNR. For example, the SNR average for the high level of firepolish is the average of the first eight rows under the S/N Ratio column of Figure 3-6. Figure 3-7 represents these averages graphically.

**Figure 3-7:** Signal-to-noise ratio averages for process parameter levels

Figure 3-6 also shows the strength response means for each of the sixteen design parameter combinations. Taking the mean averages for each process parameter level in the
same manner as for the SNRs, we obtain the averages and graph of Figure 3-8. Of particular note here is the difference between the SNR and mean average plots for the parameter "draw speed." Upon inspection, one notices that the mean averages for both levels are very close but the SNR is higher for the faster drawing speed. This difference displays one of the features of the signal-to-noise ratio transformation. The SNR places value on those levels which reduce variability in the process response. In the case of drawing speed, those trials which were drawn faster generally varied less across the four noise factor combinations.

![Graph](image)

**Figure 3-8:** Average mean strength for process parameter levels

Returning to the SNR graph of Figure 3-7, we can see how we would attempt to maximize tubing strength using Taguchi's method. It is apparent from the graph that the following levels would be selected for each process parameter:

- Acid etch............. yes
- Firepolish............. no
- Preform thickness... thick
- Furnace temperature........ high
- Drawing speed........... fast
- Capillary wall thickness.... thin
By setting the process parameters to these levels, Hewlett-Packard could produce stronger capillary tubing. They could therefore reduce tensile testing scrap, eliminate some downstream column defects, and deliver more reliable columns to their customers. In addition, stronger tubing would translate to longer average lengths between breaks, possibly allowing HP to introduce new longer columns to broaden its product line.

3.5.1.2 Results from the Alkhairy Method

Recall that the major differences between the Alkhairy and Taguchi methods of process optimization for this project were Alkhairy's use of measurements other than the SNR and his treatment of noise factors. Given that we were constrained not to run more experiments, the data used for the Alkhairy method was taken from the same experimental trials in the Robust Design matrix. It is Alkhairy's treatment of controllable noise factors as design parameters that designated from which trials the data would be taken.

Looking at the Robust Design experimental matrix of Figure 3-6, we see that the design factors occupied the following columns of the standard L16 (2^15) array:

<table>
<thead>
<tr>
<th>Column</th>
<th>Column</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acid etch.............. 2</td>
<td>Furnace temperature..... -8\textsuperscript{17}</td>
</tr>
<tr>
<td>Firepolish............. 1</td>
<td>Drawing speed............ 4</td>
</tr>
<tr>
<td>Preform thickness...... 3</td>
<td>Capillary wall thickness... -14</td>
</tr>
</tbody>
</table>

In order to model the noise factors as design factors without compromising the experimental information, it was important not to place the noise factors in those array columns which corresponded to strong design factor interactions. With six design parameters, every column in the L\textsubscript{16} (2\textsuperscript{15}) array represented at least one two-factor interaction.

\textsuperscript{17} A negative designation means that the order of levels in this column is reversed; i.e. whereas for other factors a "1" in the L\textsubscript{16} corresponds to a high level, with the designated factors a "1" corresponds to a low level.
interaction. (Only in a full-factorial design is each column isolated from higher-level interactions of other columns.) Therefore, we were forced to estimate which interactions would most likely have the strongest effects and to avoid selecting corresponding columns for the noise factors. These choices would have been easier after completion of the Taguchi analysis, but for a fairer comparison between the Taguchi and Alkhairy methods, we chose the noise columns based upon our pre-experimental conceptions of which effects might be most important. Interactions of furnace temperature, etch, and firepolish were to be avoided while wall thickness interactions could be sacrificed. Therefore, "operator" and "preform location" were modelled in columns 13 and 15, respectively. The Alkhairy array and the resulting trials selected for analysis are shown in Figure 3-9.

Taking the mean averages for each level of each process parameter, we obtain the results shown in Figure 3-10. As with the Robust Design method, we are able to identify the direction of causal relationships between the process parameters and the tubing strength. We also get a feel for which parameters are most influential and should be controlled to achieve preventive control over the process. Comparing the results from the Alkhairy experiments to the SNR averages of Figure 3-7 shows that we would have obtained the same recommendation for strength optimization using either experimental method.

By using the Alkhairy method, we reached the same conclusions with only sixteen experimental trials, compared to sixty-four using Taguchi. This fact carries obvious advantages to using the Alkhairy method. First, only one quarter of the time would have been required to complete the experiments. The reduced time requirement is a significant benefit when one considers that engineers cannot always commit much time to experimental analysis. A large time commitment might convince engineers or managers that the process improvements would not be worth the effort. In the case of the drawing process
Table 3.9: Experimental matrix for the Alkali experiment.

<table>
<thead>
<tr>
<th>Operation</th>
<th>73.04</th>
<th>62.04</th>
<th>54.04</th>
<th>46.17</th>
<th>38.17</th>
<th>30.04</th>
<th>24.17</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rejection Location</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Noise Factors</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Process Control Factors</th>
<th>Size</th>
<th>Speed</th>
<th>Temp</th>
<th>Draw</th>
<th>Influence</th>
<th>Wear</th>
<th>Polishing</th>
<th>Taper</th>
<th>Finish</th>
<th>Fine</th>
<th>Acid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>
experiment, such a decision would have meant a tremendous lost opportunity, as will be discussed in Chapter Four. Cost savings are another advantage of the Alkhairy method. Had we performed only the sixteen Alkhairy experiments, we would have saved approximately $2400 in material alone. Finally, the Alkhairy method allows for further analysis which helped to develop a predictive model for the process. This analysis is discussed in the next section.

![Graph](image)

**Figure 3-10:** Average strength response for process parameter levels using the Alkhairy method.

3.6 Progressive Control - The Predictive Process Model

3.6.1 Regression and Estimation of Effects

Although the results from both the Robust Design and preliminary Alkhairy methods helped in achieving preventive control over the drawing process, we needed to reach a level of progressive control. Preventive control would be sufficient if we were concerned simply with making the tubing as strong as possible. However, the ultimate goal of the project was to develop a model which optimized the columns operation as a
whole. We therefore wanted a model to predict the actual strength of the tubing given a process parameter combination. In other words, we wanted to be able to estimate the distribution of breaking stresses (like in Figure 3-4) which would be produced by a particular process setting. With such a model, we could weigh the strength benefits of choosing a particular parameter level against other issues associated with that level such as cost, safety, and capacity.

In order to estimate the relative effect of each parameter and the parameter interactions on the strength measure, we performed linear regression modelling using various transformations of the strength measurements as the dependent variable.\textsuperscript{18} Let us choose the signal-to-noise ratio transformation of the strength responses to demonstrate this process in a walk-through example.

The first step for each transformation was to perform ANOVA (Analysis of Variance). We chose the particular strength transformation as the dependent variable. The six main process parameters and the two-parameter interactions which corresponded to the unused columns of the L\textsubscript{16} (2\textsuperscript{15}) array served as the independent variables. Figure 3-11 shows the ANOVA results for the signal-to-noise measurements. From the ANOVA, we chose only those factors with large sum of squares for the regression. For the SNR transformation, we selected those factors with a sum of squares greater than one. By separating, or pooling, these factors, we obtain an independent estimate of the error against which we compare the estimated factor effects to determine their significance.

Chapter 3

Analysis of Variance For S/N Ratio

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>F-ratio</th>
<th>Prob</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eth</td>
<td>1</td>
<td>37.4790</td>
<td>37.4790</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frh</td>
<td>1</td>
<td>18.0675</td>
<td>18.0675</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PTk</td>
<td>1</td>
<td>2.79756</td>
<td>2.79756</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FTp</td>
<td>1</td>
<td>41.7413</td>
<td>41.7413</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DSl</td>
<td>1</td>
<td>2.61589</td>
<td>2.61589</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTk</td>
<td>1</td>
<td>0.880351</td>
<td>0.880351</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E*D</td>
<td>1</td>
<td>0.760895</td>
<td>0.760895</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F*D</td>
<td>1</td>
<td>0.924896</td>
<td>0.924896</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F*F</td>
<td>1</td>
<td>1.74419</td>
<td>1.74419</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E*F</td>
<td>1</td>
<td>8.94863</td>
<td>8.94863</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P*F</td>
<td>1</td>
<td>0.878817</td>
<td>0.878817</td>
<td></td>
<td></td>
</tr>
<tr>
<td>W*P</td>
<td>1</td>
<td>1.21700</td>
<td>1.21700</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F*W</td>
<td>1</td>
<td>1.60191</td>
<td>1.60191</td>
<td></td>
<td></td>
</tr>
<tr>
<td>D*P</td>
<td>1</td>
<td>1.85481</td>
<td>1.85481</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>15</td>
<td>121.932</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 3-11: ANOVA table for the SNR transformation of the strength response.

The regression model for the SNR measurements is shown in Figure 3-12. The constant strength is 32.61. If a factor is set at the high level, the coefficient for that factor is added to the constant. For example, if we set only acid etching and firepolishing high, we could expect to a SNR measurement of 33.08 (= 32.61 +1.53 - 1.06) from the breaking stress distribution for the tubing we produce. Figure 3-13 plots the actual SNR measurements versus the predicted strength for each combination, with the regression line shown.

To test whether a model is accurately representing all of the significant factors, we subject it to several validation tests. A model which fails one of the tests can be disputed as to its accuracy. One of the best ways to test the model is to examine the residuals (the actual measurements vs. the predicted values). Figures 3-14 through 3-16 plot the SNR residuals vs. predicted values, vs. a particular process parameter, and on a normal
probability plot, respectively. To invalidate the model in the first two plots, one looks for patterns such as residuals growing or converging as the predicted values grow or being positive for one level of the process parameter and negative for the other. In Figure 3-16, we would expect residuals to be normally distributed (approximate a straight line), and would invalidate the model if they are not.

Figures 3-17 and 3-18 show the pooled regression coefficients and plots of measured strength vs. predicted values for two more transformations. Figure 3-19 presents the same information for the raw measurements of all 64 experiments. Figure 3-20 plots these raw measurements against the predicted values from the Alkhairy regression. Appendix A contains the ANOVA results and some validation plots.

Dependent variable is: S/N Ratio
R² = 96.8%  R²(adjusted) = 90.5%
s = 0.8791 with 16 - 11 = 5 degrees of freedom

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F-ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>118.068</td>
<td>10</td>
<td>11.8</td>
<td>15.3</td>
</tr>
<tr>
<td>Residual</td>
<td>3.86375</td>
<td>5</td>
<td>0.772750</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>s.e. of Coeff</th>
<th>t-ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>32.6057</td>
<td>0.2198</td>
<td>148</td>
</tr>
<tr>
<td>Etch</td>
<td>1.53050</td>
<td>0.2198</td>
<td>6.96</td>
</tr>
<tr>
<td>Firepolish</td>
<td>-1.06265</td>
<td>0.2198</td>
<td>-4.84</td>
</tr>
<tr>
<td>PTFick</td>
<td>0.418148</td>
<td>0.2198</td>
<td>1.90</td>
</tr>
<tr>
<td>FurnTemp</td>
<td>1.61519</td>
<td>0.2198</td>
<td>7.35</td>
</tr>
<tr>
<td>DrawSpeed</td>
<td>0.404343</td>
<td>0.2198</td>
<td>1.84</td>
</tr>
<tr>
<td>FTP*DSd</td>
<td>-0.330169</td>
<td>0.2198</td>
<td>-1.50</td>
</tr>
<tr>
<td>Eth*FTP</td>
<td>-0.747856</td>
<td>0.2198</td>
<td>-3.40</td>
</tr>
<tr>
<td>WTK*PTk</td>
<td>0.275794</td>
<td>0.2198</td>
<td>1.25</td>
</tr>
<tr>
<td>Frh*WTK</td>
<td>-0.316416</td>
<td>0.2198</td>
<td>-1.44</td>
</tr>
<tr>
<td>DSD*PTk</td>
<td>0.340479</td>
<td>0.2198</td>
<td>1.55</td>
</tr>
</tbody>
</table>

Figure 3-12: Regression model for the SNR transformation of the strength response
Figure 3-13: Actual measured signal-to-noise ratios vs. predicted values.

Figure 3-14: Residuals vs. Predicted SNR values
Figure 3-15: SNR Residuals vs. each level of the drawing furnace temperature.

Figure 3-16: Normal probability plot for SNR residuals
Dependent variable is: **Strength**
R² = 99.6%  \( R^2_{\text{adjusted}} = 98.3\% \)
\( s = 1.880 \) with 16 - 12 = 4 degrees of freedom

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F-ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>3177.19</td>
<td>1</td>
<td>289</td>
<td>81.7</td>
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<tr>
<td>Residual</td>
<td>14.1401</td>
<td>4</td>
<td>3.53501</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>s.e. of Coeff</th>
<th>t-ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>48.5762</td>
<td>0.4700</td>
<td>103</td>
</tr>
<tr>
<td>Etch</td>
<td>1.83625</td>
<td>0.4700</td>
<td>3.91</td>
</tr>
<tr>
<td>Firepolish</td>
<td>-2.52625</td>
<td>0.4700</td>
<td>-5.37</td>
</tr>
<tr>
<td>FurnTemp</td>
<td>8.17500</td>
<td>0.4700</td>
<td>17.4</td>
</tr>
<tr>
<td>DrawSpeed</td>
<td>1.86625</td>
<td>0.4700</td>
<td>3.97</td>
</tr>
<tr>
<td>WallThick</td>
<td>-7.34250</td>
<td>0.4700</td>
<td>-15.6</td>
</tr>
<tr>
<td>Eth*DSd</td>
<td>3.53125</td>
<td>0.4700</td>
<td>7.51</td>
</tr>
<tr>
<td>Frh*DSd</td>
<td>1.59625</td>
<td>0.4700</td>
<td>3.40</td>
</tr>
<tr>
<td>FTP*DSd</td>
<td>3.03750</td>
<td>0.4700</td>
<td>6.46</td>
</tr>
<tr>
<td>Frh*FTP</td>
<td>4.93500</td>
<td>0.4700</td>
<td>10.5</td>
</tr>
<tr>
<td>Eth*FTP</td>
<td>-3.41000</td>
<td>0.4700</td>
<td>-7.25</td>
</tr>
<tr>
<td>PTK*FTP</td>
<td>2.09000</td>
<td>0.4700</td>
<td>4.45</td>
</tr>
</tbody>
</table>

*Figure 3-17a: Regression model for the 16 Alkhairy experiments*

We chose the model of Figure 3-18, based on the mean strength response, for the predictive process model. This model, based on 16 data points which were transformed as means from the 64 experiments, is a more accurate predictor than the SNR transformation or the 16 raw Alkhairy experiments, as Figure 3-20 shows. The regression gives a good fit with the actual data and validation tests do little to invalidate the model. This model confirms the direction of the significant individual process parameter effects found through the Robust Design and Alkhairy methods. It also demonstrates the effect of a relatively significant two-factor interaction, the interaction of acid etch and furnace temperature. The negative sign before the coefficient for this interaction in Figure 3-18a specifies that the predicted mean strength would be reduced whenever the interaction is positive, or in other words, when both of these parameters are set at the high or low level. This important
information tells us that if we neither etch the preform nor increase the furnace temperature, the strength will actually be reduced from the constant value. More importantly, it tells us that we cannot expect the strength to increase by the sum of the coefficients if we do both. When determining the tradeoffs between strength and other issues, we now know that neither etching nor increasing the furnace temperature will increase capillary strength as significantly when one of these operations is already in process. This important information would not be available to us if we had stopped at a level of preventive control.

Figure 3-17b: Actual strength measurements vs. predicted values for the Alkhairy experiments
Dependent variable is: Strength Mean
\( R^2 = 99.2\% \)  \( R^2(\text{adjusted}) = 97.6\% \)
\( s = 1.732 \text{ with } 16 - 11 = 5 \text{ degrees of freedom} \)

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<tr>
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**Figure 3-18a:** Regression model for the mean strength for the 16 process parameter combinations

**Figure 3-18b:** Strength measurement means vs. predicted mean values for the 16 process parameter combinations
Dependent variable is: **Strength**

\[ R^2 = 53.6\% \quad R^2(\text{adjusted}) = 39.1\% \]

\[ s = 11.61 \text{ with } 64 - 16 = 48 \text{ degrees of freedom} \]

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<td>Frh*WTk</td>
<td>0.219219</td>
<td>1.451</td>
<td>0.151</td>
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**Figure 3-19a:** Regression model for strength response of all 64 experiments

### 3.6.2 Confirmation Experiments

Although the validation techniques described in the last section provide confidence that the mean strength regression model will accurately predict tubing strength given parameter selection, it is important to verify the model with confirmation experiments. In the drawing experiment, this step is particularly necessary because of the confounding of interactions and main effects of the preform processing factors (etch, firepolish, and preform thickness). Recall that prior to the experiment firepolishing was considered a necessary step to increase the tubing strength. However, the experimental data suggests
that firepolishing actually degrades the strength. If this were not true, we would have expected that preforms that had been both etched and firepolished would produce stronger tubing than those preforms that had undergone neither process. This was not the case. However, one could argue that both of these combinations of etch and firepolish coincided with thick preforms in the experimental array. Possibly then, thick preforms masked the effects of etch and firepolish and influenced the determination of the negative effect of firepolishing.

![Image of a scatter plot]

**Figure 3-19b**: Actual strength measurements vs. predicted values from regression on all 64 experiments.

A confirmation experiment using the untested combination of the optimum level for each factor was drawn to test the predictive model and to test the effect of etching without firepolishing on a thick preform. The normal probability plot for this experiment is shown in Figure 3-21. The model predicted that the parameter combination of this experiment
would produce the strongest tubing of any combination. The strength measurement of 75.04 for this tubing confirmed the model's prediction.

![Diagram showing scatterplot with points indicating actual strength response measurements versus model predictions. The x-axis represents Alk hairy prediction values, and the y-axis represents strength values. The pattern suggests that the regression model based on the 16 Alk hairy experiments is not the best predictor of actual performance.](image)

**Figure 3-20**: Actual strength response measurements of all 64 experiments vs. Alk hairy predicted values. The pattern suggests that the regression model based on the 16 Alk hairy experiments is not the best predictor of actual performance.

### 3.7 Summary

The Taguchi Robust Design method and the Alk hairy method are two effective ways to bring a process under preventive control. From the experiments and analysis performed during this project, Hewlett-Packard gained a better understanding of the effects of certain process parameters on the strength and inertness of their capillary tubing. Both
of the process improvement methods specified new process settings that increase the strength of the capillary tubing. They also identified critical parameters to control to ensure that the strength remains within acceptable limits.

Both methods required some skill in designing the experiment. We needed to assess which response variables to measure and which process design and noise parameters might effect these variables. Where sacrifices were necessary, we also needed to make intelligent choices as to which information was most critical and where tests would not be as useful. However, once the experimental design was complete, we simply ran all the experimental trials and performed rather basic analysis to arrive at the appropriate conclusion. In the case of firepolishing, these methods challenged accepted ideas and prompted the removal of a process that had been degrading the tubing for over a decade. Both methods were therefore shown to be quite practical for assessing and improving manufacturing processes, and useful tools for production employees.

The Alkhairy method offers some advantages over the Robust Design method. Aside from saving time and money by requiring only one fourth of the experimental trials, Alkhairy's method aided in further analysis from which we developed a predictive process model. This predictive model brings the drawing process under progressive control whereby the relative effects of main factors and higher-level interactions are known. This predictive model is crucial for evaluating alternatives in the integrative model discussed in the next chapter.
Figure 3.21: Distribution of breaking stresses for the optimum confirmation experiment of Section 3.6.2
Chapter Four

Toward Dynamic Control-
The Integrative Strategic Model

4.1 Introduction

In Chapter Three we developed a model through statistical methods to predict the ratio of defect-free tubing to the total length of capillary tubing in a draw. Using two methods, we determined the levels of six main process factors which would optimize this ratio. Extending one of the methods, we achieved progressive control over the drawing process by quantifying the effects of main factors and their interactions, and thus could predict the strength ratio which would result from specific combinations of parameter levels. In this chapter, we will use the predictive process model in combination with other models to achieve dynamic control over the drawing process.

Recall that with dynamic control, one looks beyond the boundaries of the direct process response itself to the process' effect on other operational or economic variables. Becker, in a study at Hewlett-Packard's Microwave Technology Division, reached dynamic control over semiconductor fabrication by incorporating product revenues and costs.\(^1\)\(^9\) Process parameters were selected not to optimize solely semiconductor performance, but to optimize division profits from the processes. In this project, we will discuss the development and use of tools to analyze the effect of process parameters on revenues, costs, capacity, and capital investment decisions. These tools form the integrative model

through which we reach dynamic control over the drawing process and select the process parameter levels which optimize the strategic positioning of the Avondale columns business.

4.2 Estimating Revenues and Product Line Extensions

4.2.1 The Importance of Capillary Tubing Lengths

The predictive process model developed in Chapter 3 specifies the tubing strength which results from a particular combination of process parameter levels. The strength measure is a transformation of the ratio of defect-free tubing to the total length of tubing drawn. However, we measured this ratio from the distribution of breaking stresses plotted on a normal probability plot, taking the ratio breaks on the "vertical line" to the total number of samples. If we assume that for each sample length tested on the Instron machine only one defect contributed to the break and that the samples broke at their weakest point, then the distribution of breaking stresses follows a Weibull distribution. Studies have shown that the weakest-link model is appropriate for materials such as optical fibers and that over limited ranges, the use of the Weibull distribution is valid.20

Given that the breaking stresses do approximate a Weibull distribution, we had hoped to use the Weibull probability density function to determine the probability that a break would occur for a length of capillary passing through the tensile tester described in Chapter Two. Because the tensile tester subjects capillaries to a stress of approximately 1.5 GPa, we might have estimated the probability of a break by integrating the Weibull probability density function from 0 to 1.5 GPa. However, the 1.5 GPa limit is in the tail of the Weibull distribution, where for better experiments we have few data points. Therefore

we could not accurately estimate the break probability from this distribution with confidence. Instead, we estimate the probability from the normal probability plots, such as the one shown in Figure 3-21. We can eventually obtain more accurate estimations from testing actual production runs.

If we define N as the number of samples that break below 1.5 GPa, then if the samples are independent, N has a Binomial distribution with parameter "p" equal to the probability that the breaking stress for a single sample is less than 1.5 GPa. With independent samples, the arrival of breaks along the continuous length of the capillary approximates a Poisson process.\textsuperscript{21} To test the assumption that the arrival of defects in the drawing experiments was a Poisson process, we verified that the number of samples between two sample measurements of less than 1.5 GPa were approximately geometrically-distributed random variables. The geometric distribution is the discrete analog of the exponential, which is the distribution of the interarrival times of Poisson events. A sample of this test is shown in Appendix B. This test is equivalent to the acceptable Poisson test of checking whether or not the first-order interarrival times are approximately independent exponential random variables.\textsuperscript{22}

From the normal probability plots, we estimate the probability that any one sample breaks at a stress less than 1.5 GPa. This probability represents the percentage of samples that would contain a defect and break in the tensile tester. Because the length of each sample was approximately 2.5 meters, we can estimate the average defect rate in defects per meter by dividing the defect probability per sample by 2.5 meters for sample. For the confirmation experiment of Figure 3-21 described in Section 3.6.2, we visually extrapolate

\textsuperscript{22} Ibid., p 139.
the tail of the distribution and estimate that the tail would cross 1.5 GPa at about 0.2%. We then obtain the average number of defects per meter as follows:

\[ P(\text{break} < 1.5) = 0.2\% = 0.002 \text{ defects/sample} + 2.5 \text{ meters/sample} \]

\[ = 0.008 \text{ defects/meter} \]

The average number of defects per meter is defined as the average arrival rate in our Poisson process and is represented by the symbol \( \lambda \). The average length of tubing between breaks, then, is \( 1/\lambda \).

As the capillary tubing is tested in the tensile tester, it breaks into various lengths, the average of which is represented by the \( 1/\lambda \) measure described above. These lengths are then divided into the usable lengths for columns of the particular capillary diameter. For example, for a given draw of 210 megabore meters, we might have between-break lengths of 43, 17, 9, 41, 26, 14, 21, 4, 30, and 5 meters. These lengths would be used as follows: The 9, 4, and 5, meter pieces would be scrapped because 10 meters is the smallest length able to be processed (Even though HP sells a 5-meter column, operators process only 10-meter and longer lengths, which they may cut to 5-meters); the 14 and 17 meter pieces would be processed to make 5-meter columns; the 26 and 21 meter pieces would make 10 meter columns; and the 43 and 41 meter lengths would be used for 30 meter and 5 meter columns. Additional scrap would result from excess tubing less than 10 meters in length.

In general, all megabore tubing is cut and wrapped on baskets in the following lengths to produce Hewlett-Packard’s present megabore column line.

<table>
<thead>
<tr>
<th><strong>Tubing length</strong> (meters)</th>
<th><strong>Columns produced</strong></th>
</tr>
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<tr>
<td>10.5</td>
<td>Two 5 m</td>
</tr>
<tr>
<td>16</td>
<td>Three 5 m</td>
</tr>
<tr>
<td>21</td>
<td>Two 10 m</td>
</tr>
<tr>
<td>32</td>
<td>One 30 m</td>
</tr>
</tbody>
</table>

76
HP also planned to introduce 60-meter megabore columns, already supplied by its competitors, which would require 65 meters of tubing. When wrapping tubing from any one draw, the wrap operators' first priority is to fill the kanban for each of the four usable lengths described above. If all kanbans are filled, the operator usually divides the between-break lengths of tubing on the reel into combinations of usable lengths which minimizes scrap. For example, a 27-meter length would be wrapped on baskets in 10.5 and 16-meter lengths, therefore producing five 5-meter columns. However, because 32-meter lengths were sometimes rare, the operators would wrap as many 32-meter lengths as possible if they noticed that reels in the wrap input kanban contained mostly shorter lengths. The introduction of 60-meter columns would be extremely difficult using the present process given that continuous megabore lengths greater than 65 meters seldom passed through the tensile tester.

4.2.2 Converting Lengths to Revenues, Scrap, and New Products

In our Poisson tubing defect process, the probability of obtaining a piece of tubing of length "L" from an infinitely long reel is given by:

\[ P(0 \text{ defects in length } L) = P(0, L) = e^{-\lambda L}. \]

However, because a reel is not infinite, the probability of obtaining an unbroken length "L" becomes:

\[ P(\text{unbroken length } L) = P(0, L) \ast P(\text{at least } "L" \text{ left on reel}) \]

\[ = (e^{-\lambda L}) \ast ((D_{\text{max}} - L) / D_{\text{max}}), \]

where \( D_{\text{max}} \) is the total meters of tubing which can be drawn from a particular combination of preform and tubing size.

Using the above probabilities and the known usable tubing lengths, we developed a program which outputs the distribution of usable lengths which can be expected for a given
average unbroken draw length \((1/\lambda)\) and \(D_{\text{max}}\). The distributions as given by the program for each \(D_{\text{max}}\) combination are shown in Figure 4-1. The program gives priorities to the longer lengths, so that the average number of shorter lengths falls as the number of larger lengths grows. In other words, the program divides a random unbroken length of 59 meters into usable lengths of 32, 16, and 10.5 meters; a 66-meter length would be divided into one 65-meter length and a meter of scrap. The program therefore gives the possible number of 60-meter columns per draw. The best way to actually divide the unbroken lengths would still be determined by customer demand and profitability. The computer program which drives this usable length model, developed HP Avondale Site's Tim Kramer, is shown in Appendix C.

To demonstrate the use of the usable length model, let us assume that we set process parameters so that we obtain a defect rate, \(\lambda\), of 0.01 defects per meter in a combination that gives a \(D_{\text{max}}\) of 525. The average unbroken draw length, \(1/\lambda\), is therefore 100 meters. Using Figure 4-2(c), we see that we could then expect almost five and a half 60-meter columns, three 30-meter columns, and so on for one preform. Because the average revenue contributed by each column length is known, we can calculate the revenue contributed by each preform.\(^{23}\) Multiplying this revenue by the monthly capacity of preforms with this \(D_{\text{max}}\) gives the monthly revenues. Figure 4-2(e) specifies that we could expect about 25 meters of scrap from this preform.

\(^{23}\) Product demand might determine that the columns be divided into another combination of lengths, but for simplicity we assume here that the specified combination is feasible.
Figure 4-1(a): Column lengths as a function of the average unbroken draw length for a preform of 210 meters \( D_{\text{max}} \). The program outputs the number of columns of each length possible given the average unbroken length. Longer columns can be divided into smaller ones.
Figure 4-1(b): Column lengths as a function of the average unbroken draw length for a preform of 315 meters $D_{\text{max}}$. 
Figure 4.1(c): Column lengths as a function of the average unbroken draw length.

Expected Number of Various Length Columns
Figure 4-1(d): Column lengths as a function of the average unbroken draw length for a preform of 790 meters $D_{\text{max}}$. 

Chapter 4

Expected Number of Various Length Columns

As a function of the Average Unbroken Draw Length

Max Pre-form Yield = 790
Figure 4.10: Scrap as a function of the average unbroken draw length for preforms of each Dmax.

Simulated Amount of Scrap Material in Meters

Average Scrap per Draw (meters)
Chapter 4

The usable length model accomplishes three important tasks in our attempt to attain dynamic control. First, it provides a means for determining process yields, which will help in other models to calculate costs and capacity. Second, by determining the number of 60-meter column lengths which could be drawn from a preform, it can be used to estimate the possibility of expanding HP's current product line. Finally, it provides a distribution of tubing lengths which, by incorporating prices for the different columns, can easily be translated into revenues. The usable length distributions are dependent on the average unbroken draw length, $1/\lambda$, which through the predictive process model of Chapter Three can be estimated directly from the process parameters. Thus, by combining the predictive process model with the usable length model, we can correlate the process parameters to the columns group's revenues, total capillary process yields, and possibilities for expanding the product line.

4.3 The Capacity Model

One of Hewlett-Packard's biggest concerns at the start of the research project was how to increase the capillary tubing capacity. In order to consider meeting the capacity needs through improving the drawing process, Hewlett-Packard needed to be able to estimate the resulting capacity change before spending the funds to actually implement any process changes. In other words, HP cannot afford the time and capital required to update the drawing towers, retool, try various proposed changes, and measure the steady-state effects on drawing capacity, particularly if the improvements eventually prove insufficient. The predictive process model and confirmation experiments provided confidence that the process changes would improve the capillary strength and hence tubing yields. But another model was needed to estimate other process effects on capacity.
In order to formulate a capacity model, we analyzed the column manufacturing process, focusing particularly on the bare capillary processes prior to internal polymer coating. We measured the set-up and run times, throughput, and yields for the following processes: acid etch, firepolish, draw, recoat, tensile testing, and wrap. We also measured utilization hours and maintenance schedules on each of these operations. The analysis showed that the drawing process itself limited capacity in the present capillary manufacturing operation.

We entered the set-up and run times and other information for each of the three capillary diameters into a computer spreadsheet. Set-up and run times determined how many draws of each diameter could be completed per day. Knowing the \( D_{\text{max}} \) for each preform and tubing size combination and by incorporating the tubing yields, one can estimate the daily capacity for each diameter:

\[
\text{Output (meters)} = \text{Lots/day} \times D_{\text{max}} \times \text{yield}
\]

Through this capacity model, we were able to determine the effect on daily output of several proposed process changes. For example, using a thicker preform provides a larger \( D_{\text{max}} \) which means more capillary tubing per draw and fewer time-consuming set-ups. Therefore, the towers are actually producing tubing for a greater fraction of the working day with less direct set-up labor. Larger preforms, as shown in the predictive process model, produce stronger tubing as well, which means higher yields. Because we can accurately estimate each of the three quantities in the above equation, we can predict the new daily output resulting from the larger preform.

\footnote{Operations downstream from this process would be maintained at Avondale regardless of how HP obtained fused-silica tubing, and any bottlenecks which resulted there from increased tubing production could easily be eliminated.}
The capacity model serves to locate new bottlenecks as well. For instance, under the present process conditions, the two-shift two-tower drawing process limits capacity. The full capacity increment of adding a third tower could not be realized however without making some other changes in the operation. The model shows that utilizing the third tower would consume more preforms than could be firepolished on existing machinery. HP would either need to increase firepolishing capacity or use thicker preforms to cut down on preform numbers. The model also shows that even if enough firepolished preforms could be supplied, recoating would become a bottleneck and limit total capillary lab throughput. This very observation has led to efforts to increase the recoating capacity.

In general, with the model, we estimate that changing the following process parameters as described below will provide the most significant increases in fused-silica capillary capacity.

*Preform thickness* - Increasing the fused-silica preform wall thickness by 175% increases the $D_{\text{max}}$ by 150%. On megabore tubing, for example, the thicker preform will produce 525 meters compared to 210 for a present-sized preform. The resulting reduction in set-ups, combined with yield increases from other process changes, will increase the capillary lab capacity by about 115%.

*Capillary wall thickness* - Decreasing the capillary wall thickness by a third increases $D_{\text{max}}$ by 50%. Set-up reductions and yield increases boost present capillary capacity by close to 75%.

*Combining thick preforms and thin capillary walls* - This scenario will increase the present $D_{\text{max}}$ by 275%. The reduction in set-ups and increased yields raise present capacity by about 130% while reducing the number of firepolished preforms consumed to 5 per day.
In each of the above scenarios, operators must balance the drawing time on both towers and run draws through the shift change in order to achieve the capacity gains. In the present operation, draws which ended close to a shift change would not be restarted until the second shift began. The longer run times should facilitate this operational change.

The capacity model demonstrates the dramatic effect of process parameter selections on strategic and operational issues such as capacity planning. By selecting process parameters accordingly, HP will be able to support its growth and meet its capacity needs for several years with virtually the same equipment presently in use and without adding an additional shift. Because the new process parameter levels do not degrade the tubing strength, there is no trade-off in changing to these parameter levels. Therefore, improving the capillary drawing process does provide a viable option for Hewlett-Packard to expand its fused-silica capillary capacity.

4.4 The Cost Model

Recall that we had found a capillary vendor whose megabore tubing could be purchased at a cost lower than HP's manufacturing costs under the previous process. Because the vendor had also supplied high-quality tubing samples and had the capacity to support HP's growth, the potential cost savings made buying capillary tubing on the outside an attractive option. However, improving the capillary drawing process had the potential to reduce costs as well. Improving the yields through tensile testing and wrap certainly would reduce costs. But HP again wanted to estimate the cost reductions possible from improving the process before committing to the process changes.

To estimate the effects of various process parameter levels on the cost of capillary tubing, we again relied on a spreadsheet program. The first step was to break the cost of
the columns into those costs related to tubing and other costs such as internal polymer coating and column testing. These costs varied widely between columns of different length, diameter, and coating. On the average, capillary tubing accounted for about 40% of the overall column cost. This percentage was higher for larger diameters and longer columns. The tubing costs were in turn broken down into material costs, purchasing overhead, management overhead, direct labor, and labor-related overhead including benefits, repair and maintenance, and occupancy.

The process parameters would have the greatest effect on material, purchasing overhead, and direct labor. In the present process, material accounts for about 45% of the total tubing costs, while material overhead and direct labor each contribute another 11% each. For megabore and long columns, process changes could therefore substantially affect the tubing costs and the column costs as well. Increases in column volume would spread the other overhead costs and reduce the tubing cost per meter. We entered the various components of tubing cost in the present process into the spreadsheet cost model. Individual process parameter changes affect the cost components in different ways. The cost model captures these effects and calculates the resulting tubing cost per meter. Some of these individual process changes which most affect megabore cost are described below:

*Preform thickness* - Using thick preforms will cut megabore capillary manufacturing costs by over 12%. Thicker preforms yield about 2.5 times more tubing but cost only twice as much as normal preforms, thereby lowering material costs. Fewer setups reduce labor costs.

*Furnace temperature* - A hotter furnace increases megabore yields substantially. The scrap reduction cuts costs by about 15%.
Fiber wall thickness - 33% thinner walls reduce tubing costs by 25%. Savings come from material reductions and lower direct labor costs due to fewer set-ups.

Acid etch - Eliminating acid etch would save at least an estimated $4,000 in annual waste removal costs. In the worst case, etching could cost almost $45,000. However, scrap would increase if preforms were not etched, increasing costs by about 7%, which more than offsets the maximum direct financial savings of eliminating etching.

The cost model, combining information from the capacity and usable length models, allows us to translate process parameter levels directly into manufacturing costs. We can estimate HP's tubing manufacturing costs given specific combinations of process parameter levels, which serves two purposes. First, it allows us to determine whether or not HP could reduce its costs enough to justify the in-house production of fused-silica capillaries. Second, if the model suggests that HP should maintain capillary drawing capabilities, it provides a guideline for selecting those process parameter levels which minimize costs. The drawing process can therefore be refined without several iterations to arrive at a lowest cost operation.

4.5 Other Issues to Consider

The usable length, capacity, and cost models discussed so far provide valuable information to help select process parameter levels. However, there are other issues to consider when making decisions about process parameters. For example, one-time investments may be necessary to change to a new parameter level. Engineers should be aware of these investments and bring them into the decision process. In the capillary drawing process, changing to fat preforms and thin walls would probably require new brushless motors or a different preform drive screw to achieve stability at slower preform speeds and higher draw ratios. Adding capacity via an additional tower would cost about
$500K. Most process changes would require operator training. Safety is another concern. In the current drawing process, operators must handle dangerous acids. HP engineers and managers might consider the tradeoffs between increasing capillary strength by etching and removing the hazardous chemicals from the lab.

The most important issue to consider when choosing parameter levels is the organization's business strategy. For example, Hewlett-Packard's growth strategy initiates a need for more drawing capacity. However, if HP simply wanted to maintain its current volume but at the highest possible quality, then we would choose a process parameter level which increased strength over a level that did little for strength but increased capacity. Likewise, a strategy which called for lowest manufacturing costs and a high service level would place a higher priority on cost-saving and capacity-increasing parameter levels. One should realize however that several combinations of levels may adequately satisfy the business strategy. By integrating the predictive process model and the cost, capacity, and usable length models discussed in this chapter, we can select a combination of parameter levels which meet the business strategy while minimizing the tradeoff in other process characteristics.

4.6 The Improved Drawing Process

4.6.1 Optimum Parameter Selection

After developing all of the models described in this chapter, we applied the integrative parameter selection approach to Hewlett-Packard's fused-silica capillary drawing process. While the approach helps to estimate the effects of process parameter levels on various attributes of the operation, compare possible outcomes to the business strategy, and weigh the tradeoffs, we found that optimizing the drawing process required very few tradeoffs at all. In most of the six parameters tested, levels which increased or
had minimal effect on capillary strength also increased capacity, lowered the manufacturing cost per meter, and avoided additional investments. Likewise, levels which had little or no direct effect on capacity or cost increased the capillary strength, which indirectly lowers costs and boosts capacity through scrap reductions. The lone exception was acid etch, which is very important to increasing strength and yields, yet incurs disposal costs and requires operators to handle hazardous chemicals. Through the integrative parameter selection, we arrived at the following optimum process parameter settings:

- Acid etch............ yes
- Firepolish............ no
- Preform thickness... thick
- Furnace temperature...... high
- Drawing speed............ fast
- Capillary wall thickness.... thin

Note that this combination is the same combination listed in section 3.5.1.1 for optimizing tubing strength.

4.6.2 Implications of the Recommended Process Changes

By selecting the process levels specified in the last section, Hewlett-Packard could expect the following improvements in the overall fused-silica capillary operation:

Capacity:

Through set-up reductions, scrap reductions, and better tower utilization influenced by fewer preform changeovers, capacity on the two existing towers would be increased by about 125%. Such an increase allows HP to maintain a two-tower two-shift operation until 1995. Figure 4-2 shows the capacity gain with respect to 20% volume growth.

Cost:

Reductions in material, direct labor and associated overhead, and scrap will reduce megabore manufacturing costs by 30%. Large and smallbore savings are less substantial, primarily because there is less scrap in producing these diameters in the
present process. Given present demand, cost savings from all three capillary diameters will save Hewlett-Packard over $300K annually.

![Graph showing demand and capacity over time]

Figure 4-2: Capillary capacity scenarios vs. 20% demand growth

### Revenues and New Products:

Using the regression coefficients in the predictive model, we estimate a mean strength response of 62 for the optimum setting. Figure 4-3 shows a normal probability plot reflecting this measurement. The tail of the distribution in this plot crosses the 1.5 GPa limit at about 2.5%, which corresponds to an average between-break length (1/λ) of 100 meters. Since December of 1991, the actual production megabore has been drawn using the optimum settings except using thin preforms and thick capillary walls. (HP will incorporate the optimum settings when they obtain thick preforms.) Tubing drawn under these parameter settings has averaged between-break lengths of approximately 90 meters, adding credibility to the regression model.

From the usable length model with a $D_{max}$ of 790 meters (Fig. 4-1(d)), we estimate that with an average unbroken length of 100 meters, eight 60-meter columns can be produced per preform. If we assume that HP can sell half as many 60-meter
columns as current 30-meter demand and that sales of all other columns remain constant, they could add an extra $700K to revenues annually. Supporting the new product while continuing to supply present demand would require an extra 11% of present capacity. The new process easily meets this requirement.

Figure 4-3: Predicted breaking stress distribution for the optimum parameter setting
Chapter 4

Investments:

Given that HP would continue to draw capillary tubing, the process improvements affected several investment decisions. First, by increasing drawing capacity, HP can delay the purchase of a new drawing tower. Second, elimination of firepolishing prevents the need for a new flame lathe. (In fact, the present one can be sold.) The new process may require some investments, such as new motors, but in general less than 10% of the investment for a new tower will be required.

Vertical Integration Revisited:

The new process more than doubles capillary drawing capacity. It also reduces manufacturing costs on megabore by 30%. HP could have purchased and used an outside vendor's megabore tubing for about 90% of the present cost. Had HP decided to forego any attempts at process improvement, it would have missed a tremendous opportunity to reduce costs well below the vendor's price. Improving the capillary drawing process therefore relieves capacity constraints and makes manufacturing in-house the more economical choice. Recall that economics and capacity constraints were the major reasons that HP was considering taking the risks to purchase tubing outside, as discussed in Chapter Two. Process improvements enable HP to achieve an even better economic scenario while eliminating the risks associated with divesting of capillary drawing.

Apparently, the process improvements headed-off a potentially destructive decision. As of this writing, the possible vendor appears to be headed for dissolution, as no prospective buyers have emerged. Even with HP's business, it is doubtful that the company would survive very long. HP might have considered buying the vendor itself, but would not need the excess capacity and fiber-optics business that would come with the purchase. In addition, at least two former fused-silica capillary suppliers
have ceased drawing tubing. Meanwhile, columns competitors faced with a shrinking supplier base have begun to develop in-house capillary drawing capabilities. It is very likely that HP would have eventually found itself either restarting its own capillary operations or depending on a columns competitor for capillary tubing. Instead, with the improved drawing process, HP can investigate selling its tubing to smaller columns competitors to finance some of its own research efforts.

4.7 Summary

In this chapter, we developed a better understanding of how the process parameters affect economic, operational, and strategic issues. In this way, we achieved dynamic control over the capillary drawing process. Three models helped to identify the implications of process improvements on the overall capillary drawing operation. Through the usable length model, we can use the output of the predictive process model to estimate revenues, scrap, and the potential for broadening the megabore column product line. The capacity model translates process parameter level combinations into capacity increments. The cost model correlates these parameter combinations to the capillary cost per meter. These models, along with other concerns such as safety and capital investment requirements, help us to choose the process parameter combination through which the needs of the business strategy are best addressed.

The models and the issues they address constitute an integrative approach to process parameter selection. This approach enables manufacturers to choose parameter combinations which optimize the overall operation versus optimizing the direct process response. In addition, one can estimate the broad effects of improving a process before committing to any such optimization efforts. In the Hewlett-Packard project, the integrative approach enabled us to foresee the advantages of improving the process over purchasing
capillary tubing from an outside supplier. The improved process should save over $300K in annual manufacturing costs, more than double capacity with only 10% of the budgeted investment, and allow the introduction of new columns to broaden the product line.
Chapter Five

Conclusions

In this thesis, we sought to understand the link between manufacturing process settings, process improvements, and the strategic and operational decisions which manufacturing managers face. The research focused on improving the fused-silica capillary drawing process at Hewlett-Packard's Avondale Division. The goal of the research was to first identify key process parameters and to set and control them in such a way that optimizes the overall capillary columns operation, and second to develop a general approach to integrating statistical process improvement models with strategic issues.

To accomplish this goal, we worked toward obtaining what Hayes, Wheelwright, and Clark referred to as "dynamic control" over the capillary drawing process. In achieving dynamic control, we were able to determine the effect that each parameter has on the strength of the megabore diameter capillaries and the effects of multi-parameter interactions. In addition, we were able to estimate the effect of these parameters on such strategic issues as cost, capacity, quality, and product line extensions.

To reach dynamic control, we applied statistical process optimization methods to the drawing process. The Taguchi Robust Design method was very useful in determining the direction and relative strengths of single parameters, so that we could optimize the strength of the capillaries. With the Alkhairy method, we reached the same recommendation for the optimum process parameter settings, but with one-fourth of the data. Through linear regression analysis, we developed a predictive model which correlates process parameters to an actual strength measurement. Operational and market analysis, with the help of
computer spreadsheets, enabled us to determine the effect of process changes on broader economic and strategic issues.

Chapter Two discussed the strategic needs of Hewlett-Packard's Capillary Columns business, while Chapters Three and Four presented the methods by which we controlled the drawing process and developed the models to integrate the process settings into the strategic position of the organization. The major conclusions of this research are summarized below.

1) The Alkhairy method can be a valuable tool for process improvement and is a viable alternative to Taguchi's Robust Design method. The method succeeded in identifying the process parameter settings which optimize capillary strength. Had we used only the Alkhairy method, we would have saved time and money by performing one-fourth of the experiments needed for Robust Design.

For the capillary drawing process, furnace temperature and acid etching are the most important capillary strengthening factors. Firepolishing, which had been considered a very important strengthening process, actually decreases capillary strength. The optimum setting is expected to reduce capillary scrap by about 85%.

2) Process parameters should be set not to optimize a particular process response but in a way that best meets the business strategy and needs of the operation. Although in the drawing process there was no tradeoff between capillary strength and strategic benefits, we can look at the preform size parameter to illustrate this conclusion. Had a smaller preform size incrementally increased strength and had engineers chosen to optimize capillary strength, they would
have missed an opportunity to almost double capacity and cut megabore costs by 12%.

3) The effect of process settings on the strategic goals can and should be predicted through the use statistical and operational analysis. Models which tie process changes to strategic implications are an important tool for assessing the value of process improvement efforts and for selecting the best process parameter combination from among alternatives.

This integrative approach to process parameter selection was instrumental in the drawing process improvements. By predicting the potential capacity increases and cost reductions, we were able to justify the experiments rather than simply focusing efforts on building or purchasing a new tower and qualifying capillary vendors. This knowledge also helped us to make educated and appropriate sacrifices when designing the experiments. Had there been any tradeoffs among strength, cost, and capacity, we could weigh the relative benefits of parameter settings.

4) Improving processes through the integrative approach can produce dramatic strategic and economic benefits. Therefore, pursuing competitive advantage through process improvements can be a rewarding strategy.

Through the research efforts described in this thesis, we reduced megabore manufacturing costs by about 30%. In combination with less significant reductions on the other two diameters, these improvements will save Hewlett-Packard over $300,000 annually. We also more than doubled the total capillary capacity on the two existing towers. HP can therefore meet its growth strategy
for the next four years without spending $500,000 for a new tower. The excess capacity in the short-term can be used for additional columns research. In addition, strength increases will allow HP to introduce 60-meter megabore columns. If HP can sell half as many 60-meter columns as the present 30-meter demand at the going market price, they will add almost $700,000 to annual revenues. Increased sales supported by the added capacity may result in additional revenues.

Without the process improvement efforts, HP would have missed substantial cost savings and potential revenues. More importantly, HP would be facing the difficult and risky decision of whether or not to divest of capillary manufacturing. Given that the supplier base for fused-silica capillaries has dwindled and the instability of HP's potential vendor, HP may have found it difficult to obtain the quality and volume of capillaries necessary to meet its business strategy and could have fallen farther behind in the market. Instead, HP is poised to use its superior capillary manufacturing capabilities to gain a significant advantage over those columns competitors scrambling to develop their own capillary operations.

In conclusion, this research demonstrated the critical importance of integrating strategic issues into process improvement efforts. By investigating the strategic impact of process parameter selections, manufacturers can more efficiently and effectively control processes to improve their competitive position.
Analysis of Variance For **Strength**

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**Figure A-1(a):** ANOVA for the 16 Alkhairy experiments

![Residuals vs. predicted values for the Alkhairy experiments](image)

**Figure A-1(b):** Residuals vs. predicted values for the Alkhairy experiments
Appendix A

![Graphs](image)

**Figure A-1(c):** Alkhairy residuals vs. each level of acid etch  
**Figure A-1(d):** Normal prob. plot of Alkhairy residuals

### Analysis of Variance For Strength Mean

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**Figure A-2(a):** ANOVA for the mean strength for the 16 process parameter combinations
Figure A-2(b): Residuals vs. predicted mean strength values for the 16 process parameter combinations

Figure A-2(c): Mean residuals vs. each level of acid etch

Figure A-2(d): Normal prob. plot of mean residuals
Analysis of Variance For **Strength**

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*Figure A-3(a):* ANOVA for the strength response of all 64 experiments

![Residuals vs. predicted values for all 64 experiments](image)

*Figure A-3(b):* Residuals vs. predicted values for all 64 experiments
Figure A-3(c): Residuals vs. each level of acid etch for all 64 experiments

Figure A-3(d): Normal prob. plot of residuals for all 64 experiments
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<td>35</td>
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</tbody>
</table>

**Figure B-1:** Breaking stresses and interbreak lengths for four experiments in one of the 16 process parameter combinations.
The interbreak lengths in Figure B-1 assume breaks at a stress of 2.5 GPa. We performed a Chi-square test to test the hypothesis that these interbreak lengths are geometrically distributed. (Taking interbreak lengths between the 1.5 GPa limit does not give enough points for the Chi-square test, but the longer lengths between 1.5 GPa readings would only serve to support the hypothesis.)

The following data vector, CHIPEXP2.DATA, represents the interbreak lengths.
< 5,18,1,12,10,7,8,7,7,31,6,5,1,5,1,1,1,8 >

---

**Distribution Fitting**

---

**Data vector: CHIPEXP2.DATA**

**Distributions available:**

(1) Bernoulli  (7) Beta  (13) Lognormal
(2) Binomial  (8) Chi-square  (14) Normal
(3) Discrete uniform  (9) Erlang  (15) Student’s t
(4) Geometric  (10) Exponential  (16) Triangular
(5) Negative binomial  (11) F  (17) Uniform
(6) Poisson  (12) Gamma  (18) Weibull

**Distribution number:** 4

**Event probability:** 0.118421

---

**Chisquare Test**

<table>
<thead>
<tr>
<th>Lower Limit</th>
<th>Upper Limit</th>
<th>Observed Frequency</th>
<th>Expected Frequency</th>
<th>Chisquare</th>
</tr>
</thead>
<tbody>
<tr>
<td>at or below</td>
<td>2.077</td>
<td>5</td>
<td>5.7</td>
<td>.0786</td>
</tr>
<tr>
<td>2.077</td>
<td>8.231</td>
<td>9</td>
<td>6.5</td>
<td>.9223</td>
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<tr>
<td>above</td>
<td>8.231</td>
<td>4</td>
<td>5.8</td>
<td>.5530</td>
</tr>
</tbody>
</table>

Chisquare = 1.55389 with 1 d.f.  Sig. level = 0.212562

Comparing the computed Chi-square of 1.55389 to the Chi-square for an α of 0.05 and 1 degree of freedom, 3.841, we certainly find no reason to reject the geometric distribution. Therefore, we can be confident that the occurrence of breaks along the capillary is a Poisson process.
Appendix C

The following program produces the column length graphs of Figure 4-1.

```plaintext
%macro dosim;
  data tmp1;
  /*
    do limit = 210, 315, 525, 790;
  */
  do limit = 315 to 315;
    do lindex = 0 to 30;
      lambda = 10 ** (1 + lindex / 15);
      165 = 0;
      131 = 0;
      121 = 0;
      116 = 0;
      110p5 = 0;
      scrap = 0;
      do k = 1 to 5000;
        sum = 0;
        do while (sum < limit);
          length = min(lambda * ranexp(0), limit - sum);
          sum + length;
          165 + floor(length / 65);
          length = mod(length, 65);
          131 + floor(length / 31);
          length = mod(length, 31);
          121 + floor(length / 21);
          length = mod(length, 21);
          116 + floor(length / 16);
          length = mod(length, 16);
          110p5 + floor(length / 10.5);
          scrap + mod(length, 10.5);
        end;
      end;
      165 = 165 / (k - 1);
      131 = 131 / (k - 1);
      121 = 121 / (k - 1);
      116 = 116 / (k - 1);
      110p5 = 110p5 / (k - 1);
      scrap = scrap / (k - 1);
      output;
      drop k sum length;
    end;
  end;
run;

proc print data=tmp1;
run;
%mend dosim;
```

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Appendix C

\macro{dplots}{
\proc{scott}{data=tmpl}{
\by{limit lambda}
\proc{transpose}{data=tmpl}{out=tmp2}{
\var{l65 l11 l12 l16 l110pf scrap}{
\by{limit lambda}
\run

\symbol{1}{em40}{v=dot c=\&color1 r=1 line=1}
\symbol{2}{em40}{v=hash c=\&color2 r=1 line=1}
\symbol{3}{em40}{v=diamond c=\&color3 r=1 line=1}
\symbol{4}{em40}{v=star c=\&color4 r=1 line=1}
\symbol{5}{em40}{v=square c=\&color5 r=1 line=1}

axis logbase=10 offset=(0.5cm,0.5cm)
\labels{{"Average Unbroken Draw Length"}}
axial labels=(a=90 "Average Number of Usable Columns"
\title{Simulated Yields for Various Length Columns"}
title2 "As a Function of the Average Unbroken Draw Length"
legend1 origin=(20 pct,70 pct) down=3 mode=protect frame
values="10m (10.5")" "15m (16")" "20m (21")" "30m (31")" "60m (65")"
\labels{"Column Length" position = (top center)}

\proc{gplot}{data=tmp2}{
\where {_name_ = "SCRAP"}
\by{limit}
\label{coll limit="$Max Pre-Form Yield$"
\plot coll _ lambda _ _name_ /
\legend=legend1
\haxis=axis1
\vaxis=axis2
\frame
\vref=0 to 12\ l\vref=33\ c\vref=cyan
\run
\quit

axis logbase=10 offset=(0.5cm,0.5cm)
\labels{{"Average Unbroken Draw Length"}}
axial order=(0 to 150 by 50) minor=(n=3)
\labels{{"Average Scrap Per Draw (pieces)"}}
title "Simulated Amount of Scrap Material in Pairs"
title2 "As a Function of the Average Unbroken Draw Length"
legend2 origin=(60 pct,70 pct) down=4 mode=protect frame
values="210m" "175m" "125m" "100m"
\labels{"Max Pre-Form Yield" position = (top center)}

\proc{gplot}{data=tmp2}{
\where _name_ = "SCRAP"
\plot coll _ lambda _ limit /
\legend = legend2
\haxis=axis1
\vaxis=axis2
\vref=0 to 150 by 25 \l\vref=13 \c\vref=cyan
\frame
\run
\quit
\t\mend dplots

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Bibliography


