Applying Run-By-Run Process Control to Chemical-Mechanical Planarization and Assessing Insertion Costs Versus Benefits of CMP

by

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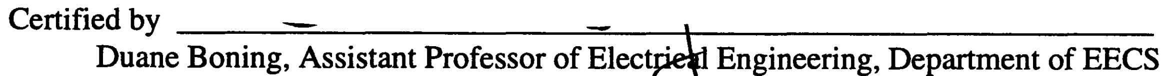

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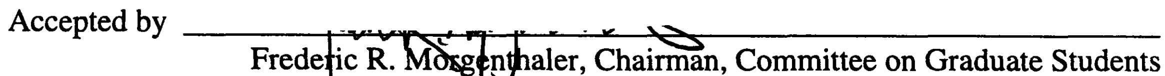

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Abstract

As semiconductor manufacturing technology progresses, it is characterized by diminishing critical dimensions, and tighter photolithographic depth of focus windows caused by the need to resolve these shrinking features. Previously inconsequential variations in the surface topography of thin films, combined with minimum required film thicknesses and greater numbers of film layers, are squeezing the effective window of operation of the photolithography process. Process steps that apply and extend existing semiconductor manufacturing techniques have been introduced whose sole purpose is to planarize the surface of a given thin film, to try to reclaim some of the process window. But these steps only affect relatively local regions of a film on a silicon wafer.

Chemical-Mechanical Polishing (CMP) is a method of achieving global film planarization, using technology adopted from the precision grinding and lapping industry. By polishing an entire wafer, it is possible to achieve an unprecedented degree of thin film smoothness. However, CMP is a process technology for which the underlying physical understanding is weak, and which has many control variables. CMP process control is at an early stage of development relative to other semiconductor processing technologies. This thesis attempts to advance the state of the practice of CMP process control by applying a new algorithmic control technology, run-by-run control (RbR), to a CMP process in a production semiconductor fab. The results obtained show that RbR is a promising approach for CMP process control, however, some practical manufacturability issues remain to be addressed for RbR to successfully move out of the laboratory and onto the factory floor.

This thesis also assesses a proposal within the host manufacturing organization, Fab 4 of Digital Equipment Corporation's Digital Semiconductor Division, to introduce CMP in place of an existing planarization process. This proposal is particularly notable because it is to introduce new technology to a production CMOS process, not to a process under development. By applying a net-present-value-focused framework, the complexity of the proposal could be managed and a common reference language for engineers and

managers was established. This framework caused new issues to be addressed that were not traditionally considered, but that were vital to evaluating the proposal: the "real option" value of switching to CMP, and the cost of disruption due to introducing new technology to the factory floor. A simple model of disruption was proposed and applied based on previous academic research on multi-factor productivity.

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Dedication

For Barb and Gabe

To the loving memories of

my mother, Beatrice Altman

and my brother-in-law, Bruce Weinberg

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Chapter 1: Introduction

1.1 Planarization and Chemical-Mechanical Polishing

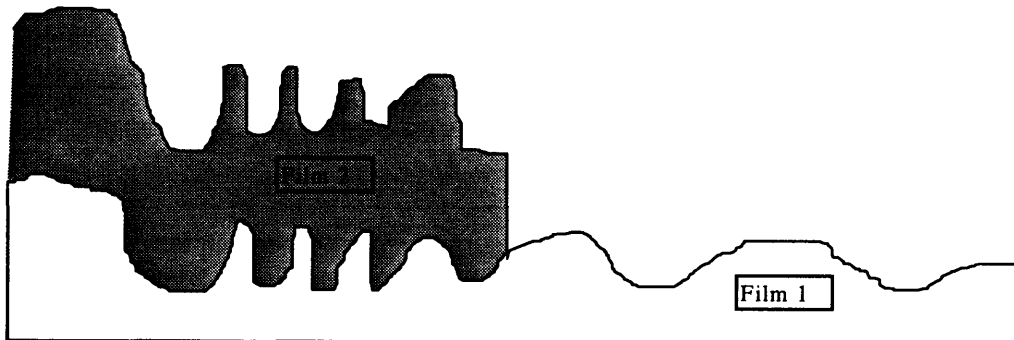
The march of silicon-based integrated circuit technology to deliver ever more functional sophistication and performance at ever decreasing prices has continued unabated for over thirty years. The primary driver of this cost/performance juggernaut has been that each new technology generation has enabled smaller devices, more densely packed and connected together on a silicon die, than the generation that preceded it.[1]

This in turn has imposed increasingly more challenging technical and business goals upon semiconductor manufacturers. Semiconductor manufacturing consists of a series of photolithographic steps, in which successive layers of metals, dielectrics, and other materials are deposited and patterned in such a way as to form electronic devices connected in a functioning circuit. The need to shrink device sizes and space them more tightly has squeezed the required minimum feature size to be photolithographically discerned down to sub-micron levels. The need to connect exponentially growing numbers of devices together to realize such complex products as microprocessors, along with the challenges of building working, reliable transistors in shrinking dimensions, have increased the number of layers and the complexity of each layer of a semiconductor product.[2]

The optics of reducing minimum feature size (also known as critical dimension, or CD) require an increasing numerical aperture (NA) in the focusing lens of the photolithographic stepper, so that it can gather enough light to give the necessary resolution to the image to be printed on the silicon wafer. However, that resolution will only be achieved within a certain depth of focus above the wafer surface. Thus horizontal CD shrinkage affects vertical focus latitude. Specifically, depth of focus is inversely proportional to NA squared, whereas CD is inversely proportional to NA.

So, for example, doubling NA to cut CD in half cuts the corresponding vertical focus range by a factor of *four* for a given exposure wavelength of light.

The surface topography of each layer of an integrated circuit reflects the topography of the layers beneath it. Topography accumulates from layer to layer, as patterning produces regions where certain layers are absent, abutted by taller regions having fewer omitted layers. The increasing number of layers in modern integrated circuits compounds this effect, to the point that the vertical topography of a complex integrated circuit could be quite severe (see Figure 1.) That is to say, severe enough to give the photolithography step insufficient process window to accommodate its rapidly diminishing depth of focus. Also, severe enough to cause many other defect modes, such as poor step coverage of deposited films and residual material after dry etching.[3] The negative impacts of topography are expected to be most severe at the highest film layers, namely those of the metal lines that interconnect the transistors; as complex logic demands three, four, or more metal wiring levels, this becomes critical.



Film 2 Selectively Deposited Over Film 1

Figure 1: VLSI Processing Topography

Therefore, there is a clear need to not only deposit and pattern films, but to planarize them, that is, to reduce the topography across the surface of a die, if not the entire wafer. Planarization techniques such as plasma etchback[4] have been developed to address this need. These techniques generally consist of depositing another film onto

a given surface layer to try to cover over its topography, and subsequent nonselective etching steps to "etch back" the combined layers to some acceptable overall thickness. This can also be supplemented by gap filling between closely-spaced structures. All of these techniques build upon existing semiconductor unit processes such as dry etching, although the added films may include specially designed materials such as spin-on glass.[5]

There are, of course, degrees of planarization of topography. The above techniques are successful at smoothing and local flattening of steps, what is referred to as "local" planarization. (Referring back to Figure 1, these techniques would have a smaller impact on Film 2 topography the wider the spacing between adjacent Film 2 peaks.) None of these techniques achieves "global" planarization, which is the absence of topography over the surface of a deposited film, across the entire wafer.[6,7] At four or more layers of metal, with technology CDs of 0.5 micron and below, the photolithographic depth of focus process window provided by the above techniques is relatively narrow. Fortunately, it is now possible to ameliorate this situation by using new photolithographic I-line steppers featuring variable NA.[8] These steppers can be set to trade off resolution for depth of focus at any layer; this is especially useful for the higher metal levels where wider lines than those needed to make transistors are acceptable.

But this approach does nothing to reduce the defect modalities caused by topographic irregularity, and in some cases it may be prohibitively expensive to upgrade to the newer stepper technology. The consensus seems to be that to enable state-of-the-art and future IC fabrication, global planarization of multiple deposited layers is required.[9] To achieve this, a different approach to planarization technology has been developed recently, Chemical-Mechanical Polishing, or CMP. CMP applies precision industrial polishing technology to sub-micron VLSI requirements. By polishing the entire wafer it is possible to achieve global planarization, and with fewer individual steps than deposition/etchback processes require.[10]

The principle of operation of CMP is to press the wafer surface to be polished against a rotating polish pad; a slurry (e.g., consisting of silica particles in water and KOH, in the case of polishing silicon dioxide) is applied to the pad as it rotates. A combination of mechanical abrasion (due to the pad and slurry particles) and chemical etch (due to slurry chemistry) causes material to be removed from the wafer surface. Because areas that protrude erode more efficiently than areas that are recessed, this process planarizes the wafer surface.

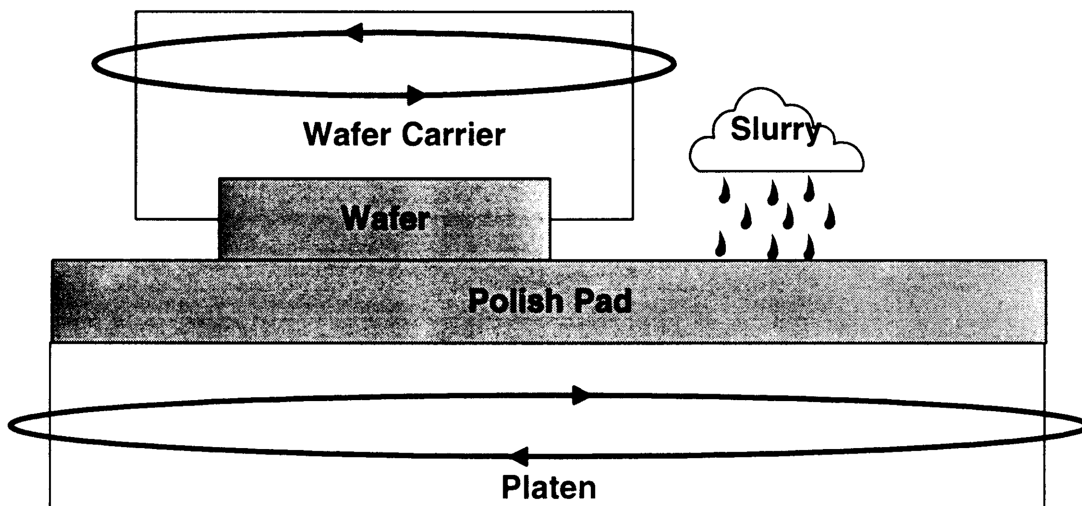


Figure 2: Chemical-Mechanical Polishing Tool (not to scale)

A diagram of a CMP tool, adapted from [11] is shown in Figure 2. The wafer is held on a rotating carrier backed by a special carrier film as it is polished. It is possible to vary the wafer and pad rotational rates, pad temperature, the downforce applied by the carrier, and many other parameters to achieve a nominal polishing rate and rate variation across the wafer. The process consumables, namely the slurry, polish pad, and carrier film, all affect process behavior and manufacturability, i.e., the ability to maintain constant process behavior over time.[12] For instance, as a wafer is polished, polish debris accumulates on the pad, reducing mean polish rate across the wafer. Pad conditioning, abrading the pad to expose fresh pad material to the polish process, is used to counter this process degradation.[13] CMP planarization is also sensitive to

pattern density, so that equivalent layers (e.g., first inter-level dielectric) on different VLSI chips can experience different polish rates under the same CMP "recipe."[14]

Despite the heritage of CMP in decades of precision industrial polishing, the detailed physical behavior of the polishing mechanism is still not fully understood.[15] Progress in CMP in the VLSI manufacturing setting has meanwhile been driven by empirical knowledge acquired by experimentation and cumulative experience. As a rough model, Preston's equation, $\frac{dT}{dt} = KPV$, is often used, especially when polishing oxide. It says that the rate of oxide removal increases with applied pressure (P) between the wafer and pad, and with increasing relative velocity (V) of the wafer with respect to the pad. K is a constant of proportionality that encapsulates other process variables such as pad temperature. Preston's equation has been shown to track experimental results in the literature,[16] but it falls short of being a complete predictive model of CMP process behavior. For example, it does not model polish rate variability across the wafer.

1.2 Problem Statement and Thesis Plan

In CMP, then, we have a process technology for which underlying physical understanding is weak, and which has many identifiable (and perhaps a few more as-yet-unknown) control variables. Not surprisingly, then, CMP process control is at an early stage of development relative to other semiconductor processing technologies. This thesis attempts to advance the state of the practice of CMP process control by applying a new algorithmic control technology, run-by-run control (RbR), to a CMP process in a production semiconductor fab.

We have already noted the need for planarity throughout the integrated circuit fabrication process, so it should not be surprising to find CMP applied at many stages of the process. However, CMP may not always be the best choice everywhere in the manufacturing sequence. This thesis also assesses a proposal within the host manufacturing organization, Fab 4 of Digital Equipment Corporation's Digital

Semiconductor Division, to introduce CMP in place of an existing planarization process. This proposal is particularly notable because it is to be a "retrofit," introducing new technology to a production process, not a process under development.

The next chapter describes CMP process control at DEC, and introduces the run-by-run control method. Chapter 3 describes the experimental approach taken to obtain CMP process models for use by the RbR controller, and the results of those experiments. The next chapter describes the method and results of testing RbR in controlling a CMP process. Chapter 5 discusses the application of a framework for assessing the CMP retrofit proposal, how such effects as performance disruption and yield improvement were modeled, and how the strategic value of CMP could be put into dollar terms. The thesis concludes with lessons learned and suggestions for future work.

Chapter 2: Process Control and CMP

Manufacturing processes transform a set of material and other inputs into a desired combination of material properties and geometry, i.e., the product. The resulting product characteristics almost always exhibit some deviation, however slight, from the target result, and so tolerances must be established. Tolerances distinguish products that are unacceptably off target from those having negligible variations, and also separate correctly functioning but "lower-performance" products from "higher-performance" ones. Manufacturing process control attempts to minimize products' deviations from their target geometry and properties, to thereby maximize the number of "within-tolerance" and/or "maximum performing" products made by a given process.

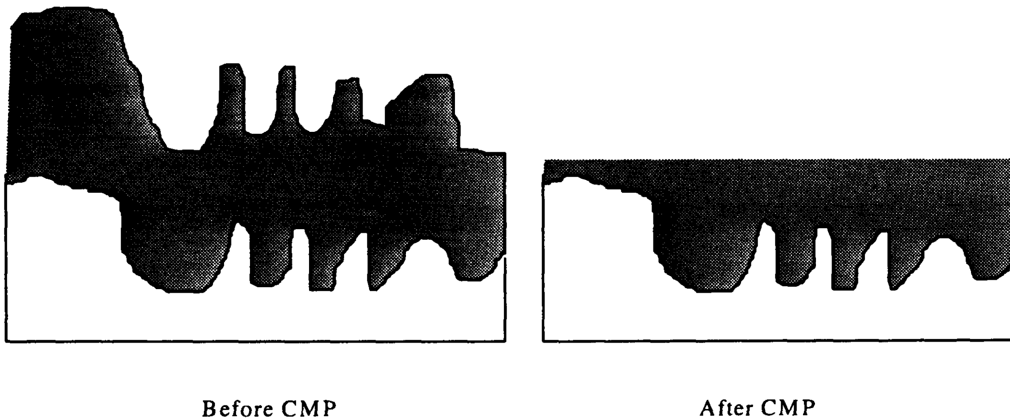


Figure 3: CMP Planarization

As shown in Figure 3, for CMP the task is to transform a thin film having arbitrary topography across a wafer into a flat film. The resulting film will possess a nominal thickness that is a function of its pre-polish thickness, the underlying topography of previously deposited films, and the planarizing performance of the CMP machine. Typically, a pattern of point locations across the wafer is selected for measurement, and

these points will be at the same location within a die*. (Thin film measurement systems such as the Prometrix 650 and 750 used in this research support such wafer pattern specification.) Therefore each pattern of points will describe a particular (replicated) vertical section of the film. It should be noted that the underlying topography is only captured by tracking multiple patterns of distinct point locations.

Some material properties of the thin film may be altered by the polishing process. For example, foreign particles previously embedded in the film may be removed by polishing, or the dielectric properties of a polished oxide may be altered at the surface[17]. These changes constitute responses to be characterized and controlled; understanding them is important to integrating CMP into the overall CMOS manufacturing process.

However, important as they may be, polishing-induced material property changes are nonetheless side-effects (good or bad) of CMP. The primary motivation for polishing is to alter film geometry. This thesis focuses on the geometry process response and how to improve its quality. To set the stage, it is necessary to first understand how polished film geometry was being controlled in Fab 4 of Digital Semiconductor at the beginning of the author's internship there, and the results that were typically obtained.

2.1 CMP Process Control at DEC

Digital Semiconductor, a division of Digital Equipment Corporation, uses CMP in its 0.5 micron CMOS manufacturing facility in Hudson, MA. In its current application, CMP polishes a deposited oxide film down, breaking through an underlying silicon nitride layer, and continuing for a pre-calculated amount of time, with the goal that a specified mean thickness for the nitride film is achieved. A nine-point pattern across the wafer is used similar to that shown in Figure 4 to obtain spatial information across the wafer†.

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*Each "point" is chosen by the process engineer such that the area covered by the point's spot size is relatively uniform; it doesn't span a pattern of features.

†A note on wafer geometry: wafers are sliced from a cylinder of silicon, and a tip of the resulting circular wafer is cut to permit the wafer to be oriented in two-dimensional space; this end is called the "flat."

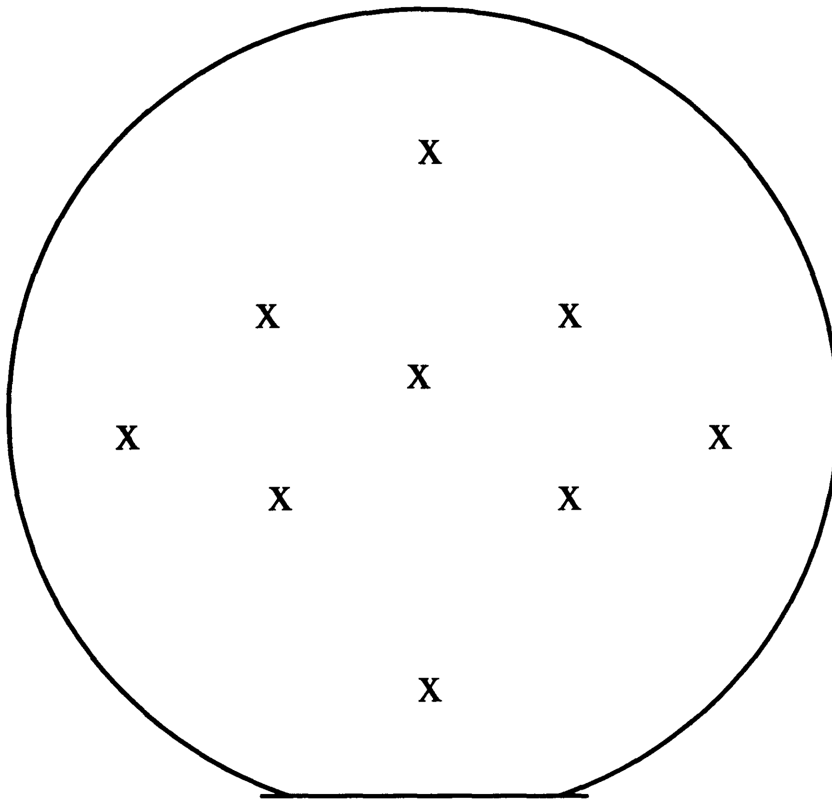

Figure 4: Approximate Film Thickness Measurement Pattern

Each point is at the same location within a VLSI chip (die). For that point or vertical section, process engineers have determined the target silicon nitride thickness to be achieved. The key feature of the nine-point pattern is that it provides, roughly, a center point surrounded by a 4-point middle ring and 4-point outer ring. The points in the outer ring are at angular offsets with respect to the middle ring, to increase the spatial information obtained. (Due to the geometry of placing die within a wafer, any collinearity of three points in the pattern is a chance occurrence.) In choosing the number of points, engineers traded measurement time and cost against ability to characterize film thickness across the entire wafer.

In this context there are (at least) two ways to characterize the film geometry after polishing:

- What is the average film thickness across a wafer and how does it vary?
- What is the range of film thicknesses across a wafer and how does it vary?

These are statistical measures that summarize the raw data obtained from the 9-point film thickness measurements. The criterion for using them is that they can be used to capture the film thickness variability within a wafer, from wafer to wafer, and from lot to lot. These are also the measures used within DEC, and so are used herein for consistency and convenience. (Qualitatively, the "average" refers to the arithmetic mean of a group of measurements, while the "range" is the difference between the maximum and the minimum values within the group. These measures will be formally laid out later.)

The same nine-point post-polish data measurements, combined with corresponding pre-polish data measurements, can be used to determine the polish rate of the CMP machine, and permit its variability to be evaluated and tracked in the same way as ending film thickness. In a manufacturing setting such data may be available as part of tracking the process that precedes CMP, otherwise it will have to be obtained as part of the CMP operation in the fab.

Having identified the process responses of interest, DEC process engineers used statistical design of experiments (DOE) and response surface techniques[18] to arrive at settings for carrier and pad rotational speed, choice of polishing pad material, and other CMP machine input parameters that would give the "best" CMP process response for polish rate. All settings were to be left unaltered by machine operators on the manufacturing line. For each lot of wafers, the time spent polishing would be calculated by the operators based on the latest machine polish rate information.

This approach was motivated by the significant drift in polish rate exhibited by CMP machines. By significant drift, I mean that the overall average polish rate, as well as the variability of the polish rate across the wafer, consistently deteriorated as the cumulative number of wafers polished rose, and could reach one or more lower control limits within a few hundred wafers. Why does this occur? Polish pads and other consumables have finite lifetimes, and their key polishing properties degrade with cumulative wafers

polished, even with pad conditioning. ("Aggressive" — frequent, lengthy, and/or maximally abrasive — pad conditioning reduces the effect, but also reduces pad life, increasing materials costs and time-consuming pad replacements.) The good news is that since this drift makes the process unstable from a "Deming" perspective,[19] it should be possible to compensate for errors without over-controlling, i.e., without making the situation even worse.

Another reason to focus on machine polish rate is the variability of the incoming oxide and nitride film thicknesses. For instance, a wafer that receives a thicker oxide deposition will require a longer polish time to achieve the target thickness. Under these circumstances, assuming an unchanging polish rate and pre-polish film thickness and then selecting a fixed polish time for the CMP process should not be expected to give a high Cpk result*.

2.2 Lot-Level vs. Wafer-Level Control

The ideal way to control the polishing process would be to measure film thickness in detail across the wafer while it is being polished, and to use real-time feedback control to adjust the polish time and other machine input parameters, for each wafer polished, to optimize resulting film variability and mean thickness. The sensing technology required is not widely available, however,[20] and was not provided by the CMP equipment vendor. (Such a real-time, wafer-level approach is being explored elsewhere, but on other processes.[21])

What is readily possible is to measure films before and after polishing. The DEC process engineering staff therefore developed a lot-level, manual closed-loop control system for CMP. This system requires that a number of unpatterned, non-product "monitor" wafers be polished, and that a number of thickness measurements be made, for every product lot.

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*Cpk, also known as the process capability ratio, is a statistical measure of the ability of the process to produce within-spec results.

The CMP machine operator plugs the information thus gained into some simple formulas that have been developed from experience. The operator uses the results to set the polishing time for each lot, roughly compensating for changing grand mean polish rates and grand mean incoming thicknesses. Starting with this time setting, a pilot wafer from each lot is first polished and measured, and the polish time for the rest of the lot is adjusted if the results so indicate. The polish time is thus fixed for all but one wafer in the same lot.

This approach keeps the average post-polish thickness for the wafers in a lot close to specified limits, even as the polish rate degrades, by adjusting the polish time. Eventually, the polish rate will degrade so far that the cycle time of the CMP machine is judged to be unacceptably low; in this case consumable items may be swapped and/or other adjustments may be performed to "reset" the machine state to a higher polish rate. The need to process monitor wafers adds to the fab's operating costs, since monitors do not become products.

Statistical process control techniques are used to deal with thickness variability caused either by incoming thickness variation or by polish rate variation. The operator waits for certain polish rate variability measures, such as the percent difference in center-to-edge polish rate, to exceed specified limits, and then acts to bring those measures back in spec, again by replacing consumable items and so on. These measures being out of spec do not correspond to out of spec polished product, but signal that it is likely that product will go out of spec soon, possibly on the next run, unless corrective action is taken. This is a practical approach for avoiding producing scrap, but unlike the case of decaying mean polish rate, the operator has no means to compensate for decaying variability as it occurs, because all other machine settings are held constant.

Since DEC first developed and applied this CMP process control approach, one commercial vendor has begun to market a CMP endpoint detection tool. This is a system that promises to signal in real-time that the target thickness for a polished layer has been

reached. With this technology, polish times could be automatically adjusted for each wafer to compensate for differences in mean starting thicknesses and polish rates. Film thickness uniformity control would remain unaddressed, however.

This endpoint detector, the Luxtron 2350, tries to capitalize on the observation that, as material *A* is polished down to material *B*, the polisher can signal the difference in coefficient of friction between the two materials. This is because the polisher adjusts its wafer carrier motor controller current to compensate for the friction change and maintain a steady wafer rotational rate. By tapping onto the carrier motor controller signal and processing it, the Luxtron 2350 tries to provide a signal that can be reliably used to detect endpoint. This approach was claimed by Luxtron to work well for CMP applications such as DEC's. However, for the case of interlevel dielectric polishing, where the oxide between two metal layers is to be polished down to a target thickness, this approach does not work because no material interface is crossed.

Over the course of 4 weeks at DEC I tested the Luxtron 2350, but found that the signal it provided did not distinguish between oxide and nitride layers at all, even when unpatterned oxide-over-nitride layers were polished. (On actual product, due to patterning, less than half the surface will have any nitride under the oxide, so polishing blanket wafers is a best-case test scenario for the 2350.) The reason was that the 2350 was designed to work with newer polisher models than those installed at DEC; the new models have different, higher-quality motors and motor controllers. We appeared to be in a "garbage in, garbage out" situation, with the polisher motor was providing an unacceptably poor input signal to the 2350.

2.3 CMP Process Control Improvement Challenges

The DEC approach works well in the factory, but the question is, can we do better, particularly with respect to three issues:

- Rather than passively watch polished films become steadily less and less uniform until the machine is reset, can we actively compensate for machine "wear"?
- Can we polish fewer or zero non-product wafers?
- Can we automate parameter compensation to reduce the chance for operator errors and permit more complex, optimized compensation calculations?

Of course, this should be accomplished while achieving as good or better mean thickness results than are already achieved by manual closed-loop control.

2.4 Run by Run Process Control

Over the last few years at MIT, as part of ongoing research into semiconductor manufacturing process control,[22] an on-line technique for process control has been developed, called "run by run" (RbR) process control[23]. The RbR controller modifies the process recipe on each lot or "run," based on data collected in the previous run. So-called "gradual mode" RbR controls the process to target in the presence of drift. The key assumptions of gradual mode RbR control are that:

1. The process exhibits systematic drift in one or more responses;
2. The process has at least one control variable that can be conveniently adjusted between runs;
3. Each drifting response (y) to be controlled can be modeled (or be transformed to be modeled) as a first-order function of control variables (x_i), i.e., $y = a + \sum_i b_i x_i$
4. There are no statistically significant interactions amongst the control variables (i.e., no $x_i x_j$ cross-terms);
5. Process drift can be modeled more or less as a change to the intercept *a*, i.e., the process's sensitivity to adjustments to x_i is fairly stable over time.

In the rest of this thesis, I will use the adjective "first-order" as short hand for the mathematical model described by points 3 and 4 above. Note that while the model can describe a simple quadratic or other non-linear relationship between the response and a given control variable (by suitable transformation of the control variable), it does not admit more complex relationships, such as a linear term *plus* a quadratic term. (While one

could transform the non-linear terms, e.g., renaming 'x^2' to be 'w', the controller would in practice try to adjust x and w separately; the current RbR software treats each control parameter as independently adjustable. William Moyne lays out the algorithmic details and limitations in his thesis[24].)

Under these assumptions, the RbR controller provides two algorithms to control the process to target. One is based on an exponentially weighted moving average (EWMA) algorithm, while the other uses the predictor-corrector (PCC) algorithm.[25] Both work to conservatively adjust the process model by updating the constant term *a* to reflect current process behavior. The EWMA algorithm locates a "new model target contour" that represents the drifting process, and selects a setting for x_i on the contour that minimizes the distance from the previous setting. The stability and robustness of the EWMA-based controller were studied[26] and found to perform well over a wide range of drift behaviors. This approach has been tested in a few semiconductor processes, such as plasma etching,[27,28] in laboratory settings. Essentially, the EWMA algorithm implements a simple integral controller.

The PCC algorithm is a two-level EWMA; the practical effect is that it provides a forecasting mechanism that can quickly and effectively react to drifts and to changes in drift rate and direction. It also suggests no changes when it sees only random fluctuations in a process response. Both algorithms are parameterized to permit the amount of history and/or the aggressiveness of the forecasting to be adjusted.

Having updated its internal model of the process using EWMA or PCC, the RbR controller then sets the control variables for the next run by solving the set of simultaneous equations that describe the responses, such that the vector of responses will be as close as possible — in a least squares sense — to the target vector of responses.

Reflecting upon the CMP process control challenges described earlier, RbR control appears to be a promising approach. It need not collect data from monitor wafers; it is

automated; it requires no new sensing, measurement, or control hardware for the CMP machine; and most importantly, it holds out the practical possibility of film uniformity drift compensation. Another attraction is that the algorithms have been implemented within a UNIX-based software environment designed for portability and ease of use[29], and can be obtained free of charge to U.S. industry.

However, the effectiveness of RbR is clearly limited by the fidelity of the first-order response model to actual process behavior. There is no research demonstrating just how much process variability must be explained by this model for RbR to work. A research group at San Jose State University and National Semiconductor is applying RbR to CMP[30], developing an optimized laboratory process and sophisticated behavior models, such as for "pad rebounding." The SJSU group has reported success using a primitive process model but has not provided details in the literature. As of this writing, no other work has been published on applying RbR control to CMP, although an R&D project by SEMATECH, University of Michigan, and MIT is underway.

2.5 Choosing the controlled response

As has been noted by other researchers of model-based manufacturing process control,[31] it is not necessarily the case that the best response for monitoring is also the best response for controlling a process. In the particular case of RbR, statistical summaries designed to give the maximum insight into process behavior will not necessarily have the first-order functional behavior described above, nor should they be required to do so. Conversely, it may or may not be particularly helpful to equipment operators, technicians, and engineers to chart a measure chosen only for its compatability with the premises of RbR.

A useful set of monitoring statistics was already being charted for the CMP process at DEC, as mentioned earlier. These summaries were obtained from raw thickness data measured at each of nine points; four wafers from each lot are sampled to collect this information. The measures for each lot were: the grand mean film thickness (TT) and the range of mean film thicknesses (RT); the mean film thickness range across a wafer (TR) and the range of film thickness ranges across a wafer (RR); the grand mean polish rate

(P); and the polish rate "nonuniformity." The first four measures concern themselves with the product result, while the last two focus on process behavior.

To define each of these measures, let X_{ijk} be the film thickness at the ith site of the jth wafer of the kth lot polished, then:

$$TT_k = \frac{\left(\sum_{i=1}^{9}\sum_{j=1}^{4} X_{ijk}\right)}{36};$$

$$RT_k = MAX\left(\frac{\left(\sum_{i=1}^{9} X_{i1k}\right)}{9}, \frac{\left(\sum_{i=1}^{9} X_{i2k}\right)}{9}, \frac{\left(\sum_{i=1}^{9} X_{i3k}\right)}{9}, \frac{\left(\sum_{i=1}^{9} X_{i4k}\right)}{9}\right)$$
$$- MIN\left(\frac{\left(\sum_{i=1}^{9} X_{i1k}\right)}{9}, \frac{\left(\sum_{i=1}^{9} X_{i2k}\right)}{9}, \frac{\left(\sum_{i=1}^{9} X_{i3k}\right)}{9}, \frac{\left(\sum_{i=1}^{9} X_{i4k}\right)}{9}\right);$$

$$TR_k = \frac{\sum_{j=1}^{4}\left(MAX\left(X_{1jk}, X_{2jk}, \ldots, X_{9jk}\right) - MIN\left(X_{1jk}, X_{2jk}, \ldots, X_{9jk}\right)\right)}{4};$$

$$RR_k = MAX\begin{pmatrix}\left(MAX\left(X_{11k}, X_{21k}, \ldots, X_{91k}\right) - MIN\left(X_{11k}, X_{21k}, \ldots, X_{9jk}\right)\right), \\ \left(MAX\left(X_{12k}, X_{22k}, \ldots, X_{92k}\right) - MIN\left(X_{12k}, X_{22k}, \ldots, X_{92k}\right)\right), \\ \left(MAX\left(X_{13k}, X_{23k}, \ldots, X_{93k}\right) - MIN\left(X_{13k}, X_{23k}, \ldots, X_{9jk}\right)\right), \\ \left(MAX\left(X_{14k}, X_{24k}, \ldots, X_{94k}\right) - MIN\left(X_{14k}, X_{24k}, \ldots, X_{94k}\right)\right)\end{pmatrix}$$
$$- MIN\begin{pmatrix}\left(MAX\left(X_{11k}, X_{21k}, \ldots, X_{91k}\right) - MIN\left(X_{11k}, X_{21k}, \ldots, X_{9jk}\right)\right), \\ \left(MAX\left(X_{12k}, X_{22k}, \ldots, X_{92k}\right) - MIN\left(X_{12k}, X_{22k}, \ldots, X_{92k}\right)\right), \\ \left(MAX\left(X_{13k}, X_{23k}, \ldots, X_{93k}\right) - MIN\left(X_{13k}, X_{23k}, \ldots, X_{9jk}\right)\right), \\ \left(MAX\left(X_{14k}, X_{24k}, \ldots, X_{94k}\right) - MIN\left(X_{14k}, X_{24k}, \ldots, X_{94k}\right)\right)\end{pmatrix};$$

Let Y_{ijk} be the initial film thickness, and T_k be the polish time for the lot, then the mean polish rate is:

$$P_k = \left(\frac{\sum_{j=1}^{4} \sum_{i=1}^{9} \left(Y_{ijk} - X_{ijk} \right)}{36 \cdot T_k} \right);$$

The polish rate nonuniformity for a wafer is measured by taking the polish rate for the site closest to the center of the wafer, subtracting from it the average of the polish rate for the points on the 4-point outer ring, and dividing by twice the mean polish rate for all nine points. This gives a nonuniformity measure from the center to the edge that ranges between ±100%. The polish rate nonuniformity for a lot is defined as the mean of the nonuniformities for the four sampled wafers in each lot.

Engineering intuition about the polish process indicated that while the means might have first-order response models, the ranges and nonuniformities were unlikely to exhibit such simple relationships to CMP process parameters. Specifically, any measure of film thickness variability would summarize the spatial variation of the polish process, which was expected to be complex. (For example, the polish rate near the wafer flat is often different from the rest of the wafer.) It also seemed risky to try to predict *a priori* the "best" statistic for controlling the variability of CMP; research on spatial uniformity control by Guo[32] suggests that using a single spatial uniformity metric to direct on-line process control may be a weaker approach than "unbundling" the metric into unsummarized spatial responses.

So rather than use DEC's CMP process charting and control measures, I decided to use the nine-point data from each sampled wafer directly, that is, to have the RbR control a nine-element response vector Y corresponding to the final polished film thicknesses at the nine measurement sites. I would specify that each site be polished to the same target thickness. In solving the resulting simultaneous equation for the best least-squares error over the nine sites, the RbR algorithm would obtain one type of "optimum" balance of mean film thickness and film thickness variation within a wafer and within a lot. (The controller would in fact treat mean thickness and thickness variation with equal importance.) The spatial variation complexity issue would be neatly sidestepped by only

modeling individual sites on a wafer: the expectation was that the response at any one site would be well-modeled by a first-order equation.

Before we leave the question of which response to control, consider the possibility of putting the polish rate at each site under RbR control instead of the final film thickness. This would be consistent with the common process control focus on machine behavior rather than on product characteristics, and harkens back to Preston's equation. However, it suffers from two weaknesses that cause me to stick with film thickness, at least for now:

- "Polish rate" is not directly measured, but is itself a summary measure, and so is potentially filtering information from the controller (e.g., initial film thickness variation);
- Polish rate would still need to be converted from "response" to "control parameter" form to enable the RbR controller to determine a lot's polish time, which poses an added complication compared to using final film thickness.

2.6 Choosing the control variables

If Y is the target thickness vector, what are the components of X? To begin, the RbR controller could adjust polish time for a given lot. But one input parameter would not be sufficient to control both the mean and the variation in film thickness. But which of the other CMP process control variables should be chosen? Here, a constraint was imposed by the manufacturing, as opposed to laboratory, setting of this work. To obtain permission eventually to try out RbR on the manufacturing line, the controller would have to avoid modifying the existing, production-qualified CMP process recipe. Otherwise all chips made while RbR was being tested would be automatically assigned "nonconforming" status, which would have made the cost of the experiment to the fab unacceptably high. So only input parameters that were unused by the process recipe were viable candidates to be RbR control variables, in addition to polish time.

Fortunately there was an unused input parameter that could be easily and accurately set by the operator from one lot to the next: back pressure. As illustrated in Figure 5, the CMP wafer carrier can apply air pressure to the back of the wafer as it is being polished, which "bows" the shape of the wafer against the polish pad. In this way, polishing rate variability can be altered without changing any other input parameter. Specifically, the center of the wafer is expected to polish faster while the outer edge is expected to polish slower than the grand mean polishing rate. While this clearly is not a fully general film thickness uniformity control variable, it does give the RbR algorithm something to work with within the stated operating constraints, and it is not obvious *a priori* that full generality is needed. (A "fully general" variable would permit thickness adjustment in any direction for any of the 9 points.)

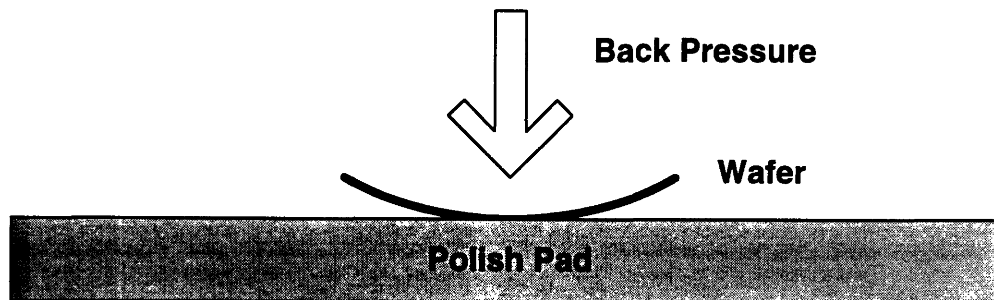

Figure 5: Back Pressure Effect

The lot-to-lot response to be controlled was therefore expected to take the form:

$$F_{ij} = A_i + B_i Init_{ij} + C_i T_j + D_i P_j + E_i P_j T_j + G_i P_j^2 + H_i T_j^2$$

for each point i and each lot j. (To get a lot's response, a number of wafers from each lot are sampled.) Here, F is the final film thickness, Init is the initial oxide film thickness, T is the lot polish time, and P is the back pressure; the same T and P are applied to every wafer in a lot. B is expected to be a positive coefficient, C a negative one, while D and E should be negative in the center and positive at the wafer edge. This equational form only makes the claim that higher-than-quadratic-order terms are not expected; the exact form of the response will be that which best explains the experimental data. The actual, empirically determined response might or might not include the P term, the PT

interaction, or higher-order terms. How close we could come to the specific first-order RbR model would remain to be seen.

The back pressure terms in the above equation deserve some comment. From a physical perspective, back pressure could possibly act in two ways. It could combine with polish time to remove more or less material, or it could act as an offset to the amount of material removed, independent of polish time. The former action corresponds to basic intuition about the continuous effect of applied pressure over time. The latter action reflects the case where the magnitude of back pressure relative to the magnitude of the polish arm downforce applied by the CMP machine (the P in Preston's equation) is particularly small. Then, if there is a back pressure effect at all, it is likely to be a result of the geometric bending of the wafer rather than the (negligible) change in effective downforce. This could yield an effect that is decoupled from polish time and is more akin to the other geometric effect, changing initial film thickness.

'Init' is a covariate, a parameter that affects the outcome but over which the CMP process has no control. It is <u>not</u> the combined nitride and oxide thicknesses, but just the thickness of the oxide over the nitride film. This is a consequence of the following: (1) the nitride film thickness was tightly controlled across the wafer, and so could safely be treated as a constant without jeopardizing the RbR experiment, and (2) to have required the nitride film thickness be available for every point, for all wafers to be sampled (if not 100% of the wafers) would have entailed a significantly more costly level of tracking than what was presently used by the fab, and at a time when the fab was looking for ways to reduce its data collection overhead. The oxide thickness at each point for each wafer could be easily obtained before a polish operation, and without imposing extraordinary costs on the fab.

The next chapter discusses the statistical design of experiments and the resulting behavioral models to be used by the RbR controller.

Chapter 3: DOE Approach and Results

This chapter begins by describing the statistical design of experiments (DOE) approach I used to characterize the F_{ij} response surface. The remainder of the chapter discusses the results of linear regressions on the experimentally obtained data. The regression coefficients are to provide behavioral models for use by the RbR controller. The reader should note that, to protect Digital Equipment Corporation proprietary data, all reported time units, be they minutes or seconds, have been multiplied by "fudge factors" to conceal actual CMP polish rates and times.

3.1 Statistical DOE

I designed an experiment to characterize the final film thickness at each of 9 wafer sites as a function of initial thickness, polish time and back pressure. In designing the experiment, I made the following assumptions:

- A number of wafers could be polished one after another in the same cassette, under different settings of polish time and back pressure.
- The number of wafers polished (experimental runs) would be small enough that CMP process drift would not affect the results. If this assumption were wrong, drift could be accounted for by an analysis of covariance, using wafer number as the covariate.
- The multiple regression results would probably show at least first-order behavior, and interactions between polish time and back pressure were quite possible.
- Initial thickness would be a measurable parameter provided by previous manufacturing steps, but not a controlled experimental design factor. Therefore it would be a covariate, a variable that affects the (regression) results but is not controllable.

If there were interactions amongst variables, and/or curvature in the response, the actual coefficients for those terms would be of interest*, so the experiment should be designed to provide such information. The experimental design need not make an *a priori* choice about which terms will be (statistically) significant: it only need be general enough to capture the highest-order terms we expect to encounter. In particular, the design must be powerful enough to capture the effect of back pressure alone and its interaction with polish time, as was discussed in the previous chapter.

The assumption that the initial oxide film thickness is a covariate for the purposes of this experiment is assailable. While it is true that in actual production the CMP process can only accept in coming thickness as an input, having been determined earlier in the manufacturing sequence, the necessarily non-production nature of the experiment could have been leveraged here. That is, I could have added special instructions to the experimental lots, requesting that they be specially processed to provide certain oxide thicknesses. In this way, I could have provided an experiment which more fully captured the response surface, whereas the range provided by the covariate approach was limited by the variability of the oxide film deposition process. However, as will be discussed, there were already significant challenges in mounting this experiment in a production setting, and I judged the incremental cost of making this improvement to be quite high in this context.

Another constraint was that the number of wafers available for experimentation was going to be limited to two lots (50 wafers total), including RbR experiments. This was a consequence of the high cost of materials and processing, and of the low priority and ever-shrinking permitted number of non-product wafers in the manufacturing line. In fact, the two lots would be available weeks apart, so it was important to get started with the first lot when it arrived.

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*Not because the RbR controller can use them, but because they could be used by the simulation package supplied in the MIT software to model the "actual" equipment being controlled.

Also, the time available on CMP tools to run experiments would be very limited. For the testing of RbR, which would require many continuous hours of processing, time on the CMP machines would have to be pre-negotiated with the production group, but that group would not hesitate to "bump" me if actual conditions in the fab warranted it. (At first, I could straightforwardly schedule time on weekends, but later the fab moved to production 7 days a week, which made it less clear when and how such experimental time slots might become available.)*

For the response surface experiments of this chapter, I decided to run as few wafers as possible, and to "jump in" at some point most convenient to the operators and as close as possible to the time when I expected to able to try out RbR, since the machine state I would capture with the response surface experiments would be changing as the operators polished product lots in the interim.

I decided to run a single experiment to characterize the process as a function of back pressure and polish time. I needed to account for more than just the presence or absence of curvature, so augmenting a 2^2 design with center points alone would not have imparted enough information. I chose a central composite design[33] (CCD) approach to capture the quadratic response surface within the practical ranges of time and pressure.

However, the CCD needed to be both rotatable and orthogonally blockable[34]. Rotatability is needed for equal estimation accuracy in all directions, and is a common requirement. Orthogonal blocking would have let the experiment be run a few wafers at a time over

*This is a good illustration of issues that arise trying to perform experiments in manufacturing settings. I sat down with the production supervisor and made the case that it was worth his while to sacrifice some productive time on the machine to permit me to run my experiments. He couldn't have cared less about the thesis research, of course, the payoff to him was the possibility of saving operator time and improving quality down the road. Even at that, this person was much more accomodating than the norm, which I attribute to his background in a pilot fab; in most manufacturing settings I would have required substantially more political muscle than I needed here. In the end for the RbR test, I was fortunate that an operator was suddenly out on a special project, leaving a CMP machine unexpectedly free for use for half of Monday and half of Tuesday over a few weeks.

separate time periods, in the event that machine access for experiments was extremely tight.

But it turns out that a CCD is difficult to block while remaining 100% rotatable. Note that a CCD requires 5 settings for each input parameter: very low ($-\alpha$), low (-1), medium (0), high (1), and very high (α). For a two-input experiment such as this, the CCD will specify some combination of center points (0,0), corner points ($\pm1,\pm1$), and star points ($\pm\alpha$,0) and (0,$\pm\alpha$). Looking at the number of corner, start, and center points in the design, it turns out that $\alpha = (corner)^{1/4}$ gives a rotatable design, while $\alpha = \left(\frac{corner \cdot (star + center_1)}{2 \cdot (corner + center_2)} \right)^{1/2}$ determines α for a two-block design. In general, it is difficult to exactly satisfy both equations. Software developed at DEC[35] suggested $\alpha = 1.2$ to give a "highly" rotatable design supportive of orthogonal blocking:

Center Point	(0,0), plus 5 replications			
Corner Points	-1, -1	-1, 1	1, -1	1, 1
Star Points	-1.2, 0	1.2, 0	0, -1.2	0, 1.2

With 4 corner points, 4 star points, and 6 center points, this gave 14 runs to be performed in randomized order, leaving 36 wafers for future experiments.

For the mapping of normalized experimental settings to actual polish time and back pressure settings, I relied on advice from DEC process engineers based on their experience with the existing CMP process. I chose allowable polish time ranges of between 80 and 140 seconds (1 second settable precision). Then, for back pressure, since too high a setting could push the wafer out of its carrier, I chose 3 psi as an upper limit, which was well below the maximum for the tool. The lower limit for back pressure was zero psi, with 0.1 psi settable precision throughout the range.

At this point, the reader should note another limiting impact of the covariate assumption for initial thickness: it will not be entirely sufficient to use regression results alone as validation that there is no interaction between initial thickness and polish time or back pressure. Again, this is because the experimental design doesn't encompass initial thickness as a control variable. However, in theory, we could fall back on simpler graphical analysis methods of the experimental results: plot the final thickness against initial thickness, with different fixed values of polish time and back pressure, and look for intersecting versus parallel lines; parallelism would tend to validate the absence of interactions, while intersections would indicate interactions. But this would require that at least two (time, pressure) pairs be replicated in the design, so that at least two lines could be drawn. Since only the center is replicated, there is insufficient data to do this. Since at the time this experiment was designed such interaction seemed unlikely, this became a tradeoff between thoroughness and cost: the expected value of the data was judged to be less than the cost of obtaining it*, since appropriate replicates could certainly have been added to the experiment.

3.2 Experiment #1

After obtaining a suggested randomized ordering from a statistical software package, and mapping the α values onto the parameter ranges, I arrived at the experimental design shown in Table 1. The next step was to obtain the experimental material. In this manufacturing setting, this consisted of:

1. Being scheduled to use one of the lots assigned to engineering experimentation—available slots were few and dwindling as volume production increased in the fab;
2. Specifying the "route" the lot would take through the production sequence until it reached the CMP step, including any pre-experiment measurements I might request to be made by the operators or "holds" to be personally made by me.

* In fact, with production pressures being what they were, it never seemed to me that this was a true option, and I never tried to get permission to do this from the production supervisor.

Run #	Wafer #	Polish Time	Back Pressure	Point
1	12	110	1.5	Center
2	2	85	0.3	Corner
3	11	110	3.0	Star
4	10	110	1.5	Center
5	15	135	2.8	Corner
6	5	110	1.5	Center
7	22	85	2.8	Corner
8	1	110	1.5	Center
9	21	110	0.0	Star
10	19	140	1.5	Star
11	16	135	0.3	Corner
12	14	110	1.5	Center
13	4	110	1.5	Center
14	8	80	1.5	Star

Table 1: Design for Experiment #1

Because of scheduling constraints mentioned earlier, only one cassette of wafers was available at this time, so the first experiment proceeded by choosing wafers from between 1 and 25,* not 1 and 50 as might have been expected. My specified route ensured that the wafers would get the same patterning they would have received had they been destined to be completed circuits, but skipped certain steps that did not impact topography, for example, ion implantation to adjust transistor device characteristics.

The first CMP run happened to be a center point, which was fortunate, because I misprocessed this wafer and had to discard it from the dataset. The misprocessing was as follows: CMP operators and engineers had noticed that the machine gave the most consistent results if it was first "warmed up" by at least one polish/condition cycle after a maintenance operation or between lots, but in loading wafers into my test cassette I neglected to insert any warm-up wafers ahead of my 14 experimental ones. So the first wafer acted as the warm-up for the remaining 13. Indeed, when the data from the first

*Actually, one wafer was mis-processed and scrapped on the manufacturing line, so there were only 24 to choose from.

wafer* was included in the regressions, less than 60% of the variability was explained by fitting a quadratic model to the data; when this first wafer was omitted, R_u^2 shot up to over 90%. Since 5 of the 6 center points remained, it was still possible to get a servicable estimate of curvature and reproducability, and subsequent experiments had results consistent with those obtained here.

The results of regressions on the data gathered by the first experiment are summarized† in Table 2, which shows the coefficients of each variable for the final thickness response at each of the 9 chosen sites on a wafer. As a reminder, the site map is illustrated in Figure 6. The regression package provided with *Microsoft Excel Version 5.0 for Windows 3.1* was used to produce these results. Here the time units are minutes.

Response	R_u^2	Intercept	Init. Thick	Time	Pressure	T*P	T^2	P^2
Site 1	92%	1200	.429	-295	0	0	0	0
Site 2	92%	1301	.454	-299	0	0	0	0
Site 3	97%	1958	.328	-824	0	0	139	0
Site 4	98%	2339	.184	-1005	0	0	189	0
Site 5	98%	1591	.552	-902	52.2	0	162	-18.8
Site 6	92%	1344	.425	-332	0	0	0	0
Site 7	99%	1820	.410	-886	45.9	0	159	-15.6
Site 8	97%	1696	.466	-862	44.0	0	147	-15.7
Site 9	97%	1296	.468	-363	0	0	0	0

Table 2: Regression Coefficient Results for 9 sites

There are two main features to look for in assessing these results with respect to the RbR controller. First, how well would a first-order model of the type needed by the RbR algorithms model the responses to be controlled; second, how often and how much is back pressure a significant factor in determining the final film thickness?

*This data was later inadvertently deleted by me from the spreadsheet, and so is not available for analysis in this thesis.

†The data and regression results and details are provided in the appendix.

It appears that using a model that omits interaction and quadratic terms will have high fidelity to the behavior model obtained via linear regression. None of the responses demonstrates a statistically significant interaction between polish time and back pressure! In addition, as compared with those responses that have no squared terms, those that do also possess higher linear coefficients, and opposite-signed squared coefficients, so that qualitatively their behavior is not all that far removed from those "linear" responses.

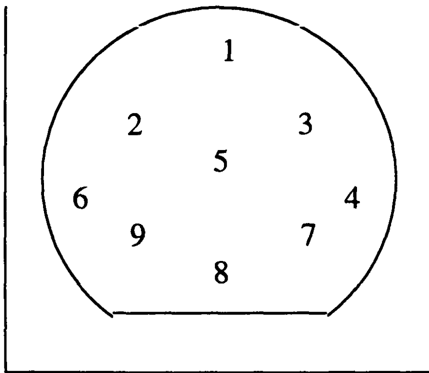

Figure 6: Wafer Site Map

In fact, if the regression calculations are repeated for sites 3,4,5,7, and 8 with a model that has zeros for the quadratic terms, the resulting R_a^2 is still over 90%, as summarized in Table 3. Since this now is a first-order model — there is still no statistically significant interaction between time and pressure — tt is the coefficients in this table that would be used by the RbR software, along with those of sites 1,2,6, and 9 from the previous table.

Unfortunately, for the RbR model, the back pressure term is only present in two responses, and its effect is small: at maximum pressure of 3 psi it predicts a relatively small change in angstroms of thickness compared to the change possible by altering polish times. Further, only the expected increase in the amount of film removed from the center is observed at all, while the predicted edge polish braking effect is not seen. This all means that the back pressure variable does not appear to provide a particularly dynamic nor general thickness variability adjustment knob to the RBR controller.

Response	R^2_a	Intercept	Init. Thick	Time	Pressure	T*P	T^2	P^2
Site 3	96%	1346	.429	-317	0	0	0	0
Site 4	94%	1553	.281	-312	0	0	0	0
Site 5	94%	939	.647	-310	-7.78	0	0	0
Site 7	94%	1292	.431	-305	-2.25	0	0	0
Site 8	94%	1200	.487	-322	0	0	0	0

Table 3: Linearized Regression Results

However, events in the manufacturing line caused this conclusion to be premature. First, machine maintenance records revealed that, because back pressure was not part of the production CMP recipe, it had never been calibrated since the time that the machine was originally delivered from the vendor over 18 months earlier, because no one had bothered to include it in the regular preventive maintenance worklist. So this experiment had been run with a questionable input parameter. Second, a major, annual preventive maintenance procedure was carried out by factory technicians just a few days after this experiment was performed. Typical procedures include leveling the polish platen and similar activities that require the machine to be down for an extensive period. So the state of the machine had just been significantly altered relative to where it had just been characterized, adding further doubt about the usefulness of the experimental results. I decided that the results were enough in question to warrant repeating the experiment, using newly-recalibrated back pressure and a freshly post-annual-preventive-maintenance CMP machine.

3.3 Experiment #2

By now the second cassette of experimental wafers had arrived, so the experiment was simply repeated using the same randomized wafer selection as for the first cassette. Since the cassettes will not have undergone *identical* processing, some component of variation in the results will be due to differences between wafers processed in different cassettes, however, there is no particular need to specifically account for this difference. Table 4

summarizes the regression results; again, the RbR first-order model permitted an excellent fit to the data, and the coefficients appear qualitatively similar to those produced by the first experiment. (In fact, the equipment technicians reported that back pressure had been only moderately out of calibration.) Unfortunately, this also means that the back pressure variable is still insufficient to permit RbR to improve the variability of the polished film thickness. Here, only one site is sensitive to back pressure, with a weak, albeit improved, effect on the result.

Response	R_a^2	Intercept	Init. Thick	Time	Pressure	T*P	T^2	P^2
Site 1	92%	1428	.450	-465	0	0	0	0
Site 2	93%	2160	0	-435	0	0	0	0
Site 3	95%	1563	.366	-440	0	0	0	0
Site 4	97%	1473	.406	-449	0	0	0	0
Site 5	93%	1398	.429	-354	0	0	0	0
Site 6	97%	1531	.357	-484	18.1	0	0	0
Site 7	95%	1544	.356	-425	0	0	0	0
Site 8	96%	1425	.438	-390	0	0	0	0
Site 9	97%	1452	.510	-548	0	0	0	0

Table 4: Repeated Regression Results

Thus it appeared that the response surface for the CMP process was such that it was basically insensitive to back pressure.* At this stage I judged there were three main options for going forward. First, I could proceed with RbR control with the polish time control variable alone. But this would have meant only controlling mean polished film thickness, and not nonuniformity, because the RbR controller would not have sufficient degrees of freedom at its disposal to do any better. Besides, since the existing DEC CMP process control method did this already, the costs of such a demonstration would have been difficult to justify. Second, I could put the production recipe itself in bounds for

*Subsequent investigation by DEC process engineers uncovered a technical basis in the recipe for this behavior, but the details are proprietary. Generally, a number of process parameters could be set and/or interact such that they could swamp the back pressure effect.

experimentation. This would have entailed more materials and machine time than was feasible to obtain within the remaining project schedule, especially given the increasing fab production rates and consequently decreasing machine availability for engineering activities. The third choice was to move to a different CMP process. This was the path I selected, but it would come with its own set of issues, as discussed next.

3.4 Back End CMP Experiment #1

The process engineering group was in the midst of developing another CMP process for use in the fab. This was to planarize inter-level dielectrics between metal layers, a common CMP application. Since the metal lines used to connect transistors are normally deposited above the films that form the devices, the manufacturing process is sometimes spoken about as having a "front end" (processing to make devices) and a "back end" (processing to connect devices.) Thus the application was referred to as "back end CMP."

There were both pluses and minuses to switching focus away from the production CMP application to back end CMP:

+ Polishing inter-level dielectric is a mainstream CMP application, and so would be a good vehicle for "showcasing" RbR control of CMP;
± A single CMP machine was dedicated to back-end development, so it would be easier to access for experiments than the production machines had been, but it suffered from chronic wafer-handling problems and so would be more difficult to operate;
– Since back-end CMP was still under development, process engineering was not as far down the learning curve as it was on the production CMP process, for instance, in successfully "resetting" the machine when polish rate nonuniformity exceeded specified limits;
+ Experimental wafers were cheaper and easier to obtain, and unpatterned films would be suitable for data collection because no patterned wafers had yet been tried on the back-end recipe anyway;
– There was no baseline SPC data against which to judge the performance of the RbR controller;

- There would be no chance to demonstrate RbR on the manufacturing line, on actual products.

I devised an experimental strategy that entailed running the response surface characterization experiment just after fresh consumables had been installed, at a time when the machine was behaving "well." Also, as soon as possible after obtaining a regression model, I would begin to test the RbR controller. (In fact, since the RbR controller would require some initial conditions about the state of the machine, I planned to use replicated center point data freshly obtained from the experiment to represent a "lot" that had just been polished. This data, plus the incoming film thickness of the first lot to be polished under RbR control, would serve as the initial conditions.)

There was another experimental advantage that I derived from having had more experience in the fab than when I had designed the original 14-wafer central composite design. As I discussed earlier in this chapter, although the incoming film thickness is a covariate for CMP on the production line, it is possible to treat it as a control variable *when performing a designed experiment.* I now had the practical option of having wafers individually deposited with specified thicknesses of unpatterned inter-level dielectric, since my experimental wafers would not be prepared as part of normal production. I could use engineering estimates of how much ILD film thicknesses would vary to give likely upper and lower bounds, and from this design an experiment that would permit the response surface as a function of pre-polish thickness to be more confidently characterized than it had been in the 14-wafer case.

I specified that a nominal 15 kÅ-thick unpatterned ILD film would be polished down to a 12.5 kÅ target thickness under RbR control. Based on engineering experience, I set the lower and upper bounds for the pre-polish thickness to be 14 kÅ and 16 kÅ, respectively, for the purposes of the experimental design.

This time around I would have a fair degree of scheduling control of the CMP machine, so making the experiment suitable for orthogonal blocking no longer appeared necessary. Hence, I settled again on a uniform-precision, central composite design, with $\alpha=1.68$, as indicated by Table 16-8 of Reference 34. This design uses 6 center points, 6 star points, and 8 corner points. While the back pressure range did not change, the polish time uses a wider range [60 to 240 seconds] to capture a broader swath of the response surface compared with the front-end CMP experiment. The resulting experimental design is shown in Table 5. Note again that initial thickness is now a controlled variable, so the values in the table are designed.

As before, nine points are selected on the wafer surface to provide nine responses to be controlled under RbR software. The exact same points are not selected, however, since there is no pattern involved, but their approximate locations on the wafer are still designed to provide a central point, four points making a middle ring, and four points making an outer ring. Using software built into the Prometrix 650/750 film thickness measurement system, the following pattern was selected as shown in Figure 7, for its symmetry and avoidance of a single point at the wafer flat.

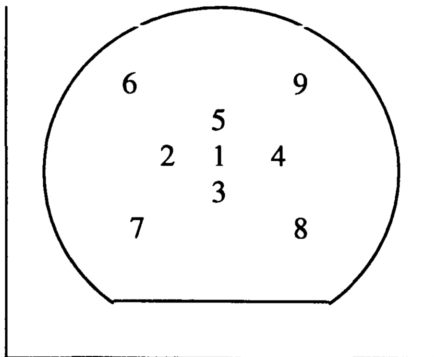

Figure 7 : Back-end CMP Wafer Response Pattern

An inconvenient aspect of this experiment was that the film thicknesses provided by the diffusion operation could never exactly match those specified in the experimental design. At each of the nine sites, the actual film thickness was found to be as much as hundreds of angstroms different from the specified thickness. This means that the span of the

covered response surface is different from that intended by the experimental design. Cost and time constraints precluded going back to the diffusion operation and attempting to get more precise film depositions.

Run #	Initial Thickness	Polish Time	Back Pressure	Point
1	14405	97	2.4	Corner
2	15000	150	1.5	Center
3	15000	150	1.5	Center
4	15000	240	1.5	Star
5	15000	150	1.5	Center
6	14405	203	0.6	Corner
7	14405	97	0.6	Corner
8	14405	203	2.4	Corner
9	15000	150	1.5	Center
10	15595	203	2.4	Corner
11	15000	150	1.5	Center
12	15000	150	0.0	Star
13	15000	150	3.0	Star
14	15595	97	2.4	Corner
15	15000	60	1.5	Star
16	15000	150	1.5	Center
17	14000	150	1.5	Star
18	15595	97	0.6	Corner
19	15595	203	0.6	Corner
20	16000	150	1.5	Star

Table 5: Back-end CMP Response Surface Experimental Design

The regression results of the experiment are summarized in Table 6. The regression used the measured initial film thickness values. The intercept term, plus all interaction and 2nd-order terms, were all zero, and are omitted from the table for brevity. The initial thickness coefficient is essentially unity.

From a physical perspective, polishing a single-material, unpatterned film having little topographic variation produced a constant polish rate that was simply the difference

between beginning and ending thicknesses, divided by the polish time. One could infer from this that the richer behavioral models seen in the previous CMP experiments were driven by the presence of patterning, more topographic variety, and/or by polishing more than one material.

Response	R_u^2	Init. Thick.	Time	Pressure
Site 1	94%	1.003	-1216	0
Site 2	94%	.998	-1248	0
Site 3	94%	1.005	-1291	0
Site 4	92%	.995	-1276	0
Site 5	94%	.996	-1265	0
Site 6	93%	.993	-1150	110
Site 7	91%	.979	-1120	122
Site 8	92%	.976	-1145	183
Site 9	92%	.999	-1094	0

Table 6: Back-end CMP Coefficient Regression Results

A disturbing aspect of these results, though, is that there is no apparent back pressure effect at the center of the wafer, only at the edge, and that only one-third of the sites seem to be back-pressure sensitive at all. This did not bode well for back pressure acting as an effective film variability control parameter. However, as it happened, just after this experiment was run, the CMP process technician uncovered significant polish rate nonuniformity problems on the machine. A major maintenance activity ensued to repair the machine, until acceptable results were once again achieved. The machine's state having now been significantly altered, I judged that this invalidated the model I had just obtained with the latest experiment.

Therefore, as soon as possible after the repair work was completed, I ran a second response surface experiment, but this time I returned to a 14-wafer CCD design, primarily because it would have taken extra time to get the needed special-thickness wafers made up, I had a ready supply of 15 KÅ film wafers, and I wanted to get started on the machine

while it was still behaviorally stable. (I was also feeling comfortable, based on the previous experimental data, that this time around I could omit a rigorous accounting for pre-polish thickness interactions.) The other change I made was using the standard value for a rotatable design, no longer concerning myself with orthogonal blocking. The site selection on the wafer surface was unchanged.

3.5 Back End Experiment #2

The experimental design, and its summarized regression results, are shown in Table 7 and Table 8, respectively. Again, the intercept, interaction, and quadratic terms were zero, and are omitted from the table for brevity.

Run #	Polish Time	Back Pressure	Point
1	150	1.5	Center
2	97	0.6	Corner
3	150	3.0	Star
4	150	1.5	Center
5	203	2.4	Corner
6	150	1.5	Center
7	97	2.4	Corner
8	150	1.5	Center
9	150	0.0	Star
10	240	1.5	Star
11	203	0.6	Corner
12	150	1.5	Center
13	150	1.5	Center
14	60	1.5	Star

Table 7: 14-Wafer Central Composite Rotatable Design

This time, the back pressure impact is stronger, but four out of the nine sites are still unaffected. Still, in looking at the geometry of the sites, we see an increase in material removal at the center with applied back pressure, and a decrease at the wafer edge, so it is not surprising that the effect in the middle ring area of the wafer is neutral.

Response	R_a^2	Init. Thick.	Time	Pressure
Site 1	90%	1.005	-1152	-91
Site 2	91%	1.000	-1233	0
Site 3	90%	1.014	-1281	-110
Site 4	91%	1.003	-1308	0
Site 5	91%	.993	-1228	0
Site 6	89%	.985	-1172	205
Site 7	89%	.984	-1211	130
Site 8	90%	.981	-1221	197
Site 9	86%	1.000	-1163	0

Table 8: Final Back-end CMP Response Surface Coefficient Results

To summarize these results, recall the general form of the response from the previous chapter:

$$F_{ij} = A_i + B_i Init_{ij} + C_i T_j + D_i P_j + E_i P_j T_j + G_i P_j^2 + H_i T_j^2$$

The regression model that best fits the data has the A,E,G, and H coefficients set to zero, and B set to 1. The effect of back pressure as a supplement to polish arm downforce (the PT cross-term) appears to be negligible, but it does exhibit a geometric effect (the P term) in certain locations on the wafer.

At last I could proceed to test out RbR control of CMP, using the above model and the results of the six center points as the "initial conditions." The next chapter describes the design and results of this testing.

Chapter 4: RbR Experimental Approach & Results

As part of its research into the on-line control of semiconductor manufacturing processes, a research group led by Prof. Duane Boning at MIT's Microsystems Technology Laboratories has developed a UNIX-based software package with the following capabilities:[36]

- implements parameterized EWMA and predictor-corrector control (PCC) algorithms;
- provides an "equipment simulator" that can be perturbed with noise and drift; and
- provides a graphical user interface for ease of use.

The equipment simulator gives the RbR software a "virtual machine" that it can attempt to control, under various machine behavior circumstances. It requires a behavioral model to be supplied just as does the RbR controller; this too will usually be derived from a response surface characterization experiment and regression. The simulator will accept essentially any polynomial behavioral model the user cares to supply, as contrasted with the first order model required by the RbR controller. This capability is highly beneficial when a substantial portion of the machine's behavior is described by interaction and supra-linear terms — it is probably unclear in such a case how well the RbR software can control such a non-linear machine without first simulating it.

There was no such discrepency for the back-end CMP experiment: machine behavior was well-described using purely linear, non-interacting terms. Therefore the model held by the RbR controller and the model held by the simulator would be identical. If no noise were introduced, one would expect the RbR controller to give ideal results. Adding white noise and drift would not especially reveal anything about the ability of the RbR method to work beyond the theoretical treatments in the literature[37] which analyze EWMA control under the same types of perturbations. In fact, we expect the more powerful PCC algorithm to work well in this situation. I judged that the most revealing thing to be done at this stage would simply be to proceed to polish as many wafers as possible under RbR control. (From the perspective of making the case for RbR within the factory, I also

sensed that simulation results would not be anywhere near as compelling to manufacturing personnel as "real" results.)

The back-end CMP process was still under development, and so there was as yet no stable process from which to infer "typical" amounts of noise and drift. However, data from the front-end CMP process could illustrate how one stable CMP process was currently behaving. I arranged to have all the wafers in two arbitrarily chosen front-end CMP lots measured, as follows:

(1) I selected nine sites per wafer to match the ones used by production in its own tracking;

(2) At each site, production personnel measured the deposited nitride film thickness A, the subsequent deposited oxide film thickness B, and the post-CMP nitride film thickness C;

(3) Noting the polish time T for each lot, I calculated a "mean polish rate" for each wafer in a lot as the average of $\left((A+B-C)/T\right)$ over the nine sites; and

(4) I also calculated the natural log of the standard deviation of polish rate for each wafer (because this is expected to be a roughly Gaussian distribution, unlike the standard deviation).

The resulting charts* suggest that the qualitative degree of drift may be substantial for the front-end process: with a standard deviation (σ) of about e^{-3} or 5%, the polish rate appears to deteriorate by as much as two σ per lot. This is still within the capability of the PCC algorithm to track the overall trend. While this may or may not be predictive of the back-end process, it at least suggests that the RbR controller should not be ruled out *a priori.* The real issue was therefore how long and how well the combination of back pressure and polish time could control polished film uniformity under perhaps rapidly deteriorating machine conditions.

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*I have converted polish rate data into a percentage of a nominal rate to protect DEC proprietary data.

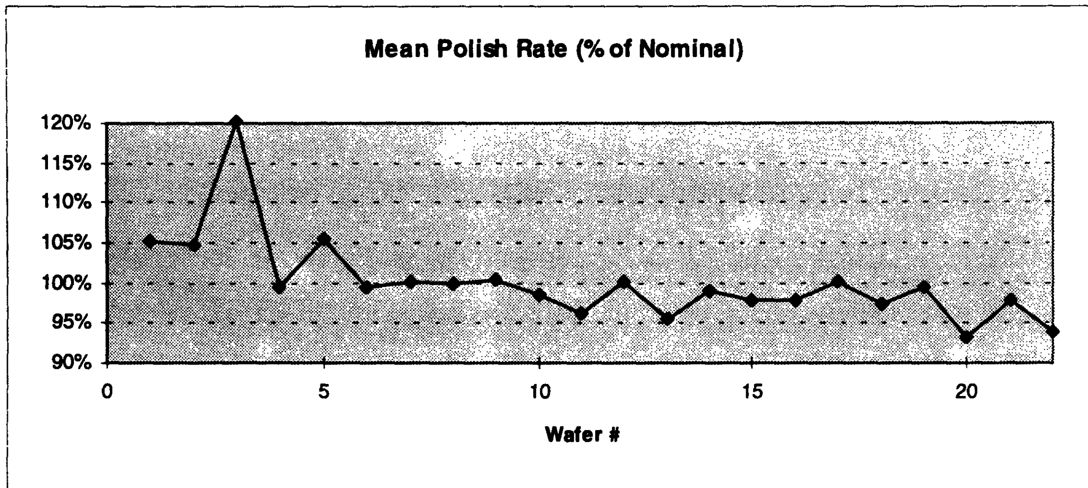

Figure 8: Front-end CMP Lot #1 Polish Rates

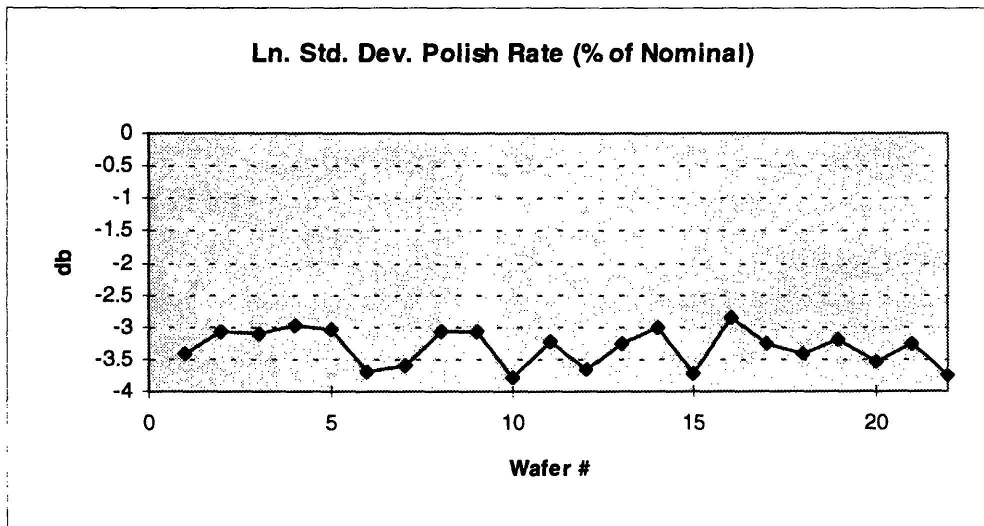

Figure 9: Lot #1 Polish Rate Variation

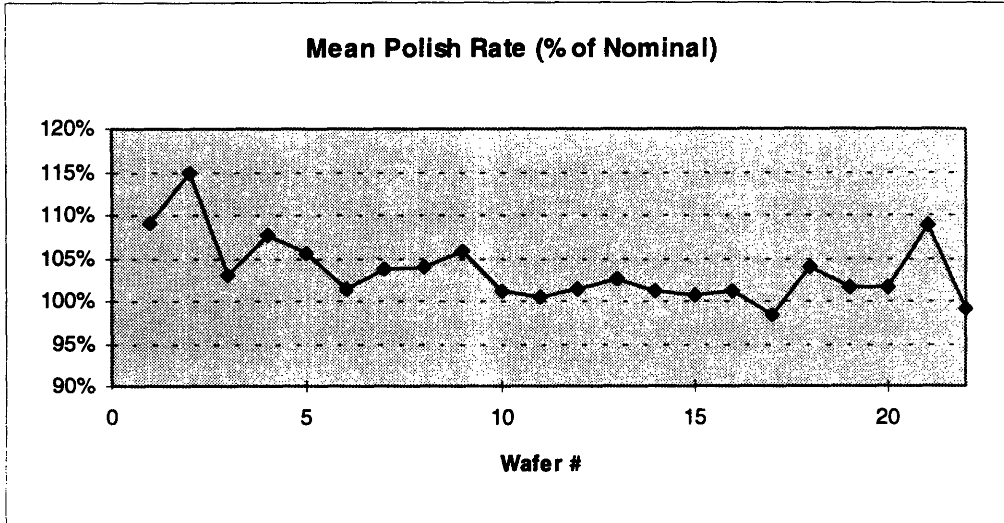

Figure 10: Front-end CMP Lot #2 Polish Rates

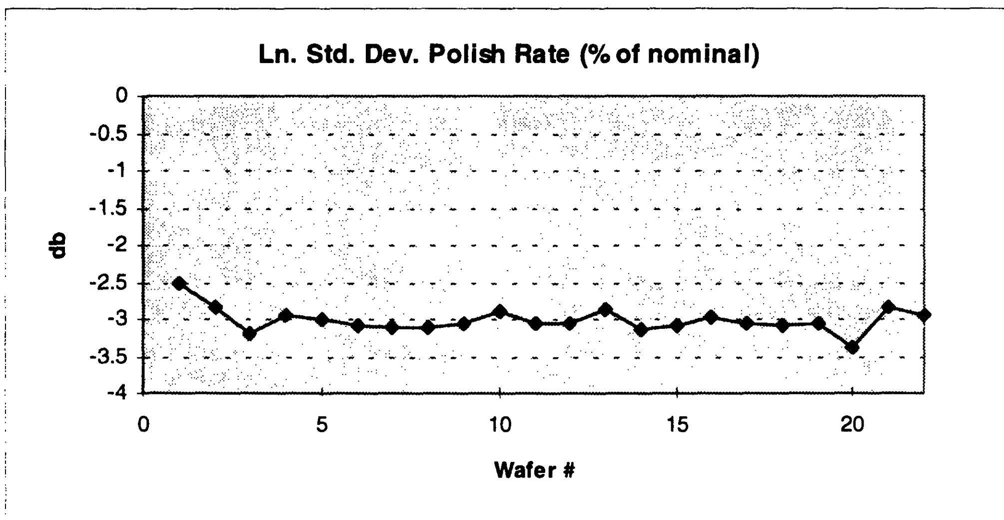

Figure 11: Lot #2 Polish Rate Variation

4.1 RbR Test

As I noted earlier, the PCC algorithm consists of a two-level EWMA that promises superior ability to compensate for systematic drift compared to a single-level EWMA controller. The model update equations of PCC* for each run t are:

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* This notation is taken from Moyne's thesis.

$$n_t = \alpha(y_t - Ax_t) + (1-\alpha)n_{t-1}$$
$$d_t = \beta(y_t - Ax_t - c_{t-1}) + (1-\beta)d_{t-1}$$
$$c_t = n_t + d_t$$

where n is the noise estimate, d is the drift trend estimate, c is the updated constant term in the RbR model, y and x are the measured responses and control variables, respectively, and A represents the (unchanging) model coefficients of x. The algorithm's behavior is controlled by the parameters α and β.

For this test, I set the two PCC algorithm parameters at $\alpha = 0.5$ and $\beta = 0.9$. The α parameter controls over how many previous lots EWMA-style averaging will occur — at 0.5, only the last 5 or so lots would have a major impact. The β parameter sets the sensitivity of the trending function — at 0.9 only the last two lots would have a major impact. The β setting would thereby permit good tracking of changes in response slope. In contrast, setting β low for a leisurely tracking would not have resulted in much practical algorithmic difference from a simple EWMA integral controller.

Each polished lot was to contain 25 wafers, all but 4 of which were to be treated as dummies, that is, dummy wafers are polished but not measured. All wafers started with a 15 kÅ unpatterned ILD film; after being used as data, wafers were reused as dummies, so that ultimately I was able to polish 200 wafers while only expending a fraction of that number. I placed the data wafers such that they were evenly spaced across the cassette and the last wafer polished would always be a data wafer. The reasons I chose this approach instead of placing 4 wafers at random anywhere in the cassette for each run were:

- To ensure that sufficient warm-ups would always be performed before a data wafer;
- To ensure that the results of the last wafer polished in the lot (the one experiencing the most accumulated drift, if you will) would be included in the response being controlled; and
- To ensure that the response being controlled consistently reflected the drift across a lot.

Note, however, that variation due to within-cassette placement cannot be accounted for as it would be with random placement. In hindsight, some compromise, such as random selection from inside each of 4 quartiles in the cassette, would have ameliorated this problem. In production, if it is desired to engage in SPC charting of aspects of the CMP process using the same raw data (monitoring, as opposed to controlling) it would also be helpful to have randomized locations within a lot.

I used only 4 wafers per lot due to the sampling precedent set in the front-end CMP process, that is, I wanted to be able to demonstrate the feasibility of RbR control without having resorted to more expensive sampling than was already tolerated by the manufacturing organization. This sample size is not entirely sufficient to characterize within-a-lot variability[38] (which tends to make the above wafer placement discussion a bit beside the point) but it is adequate to capture lot-to-lot variability, which is the prime focus of RbR control.

During this test, nine lots were polished under RbR control. On each run, the software would accept as inputs:

- the four-data-wafer average of the post-polish ILD film thickness at each of the nine sites for the previous lot, and
- the four-data-wafer average of the pre-polish ILD film thickness at each of the nine sites for the upcoming lot.

The target thickness for each site was set the same, at 12.5 kÅ. No pad replacement or other machine maintenance activities were permitted to be performed during this experiment, so that the data could be viewed as having been collected "back-to-back," however, due to the length of time required to pre-measure a lot, polish it, measure it, exit the fab, operate the software, re-enter the fab, and so on, only two or three lots were polished per day, with the machine left idle overnight.

4.2 RbR Test Results

To assess the results of the test, I used six different measures, all of which are already used in some form at DEC to track the front-end CMP process. Thus, I would have a common basis to discuss the results with DEC personnel, even if I could not use the front-end data as a direct baseline for comparison. (For instance, it would be specious to compare the Cpk for the back-end CMP process under RbR control to the Cpk of the front-end process without RbR control, and there is no Cpk established for the back-end CMP process still being developed.)

As described in Section 2.5, the measures for each lot were: the grand mean film thickness TT and the range of mean film thicknesses RT; the mean film thickness range across a wafer TR and the range of film thickness ranges across a wafer RR; the grand mean polish rate P; and the polish rate nonuniformity NU. The first four measures concern themselves with the end result of polishing, while the last two focus on CMP machine behavior.

For this test, the polish rate nonuniformity for a wafer is measured by taking the polish rate for the site closest to the center of the wafer (site 1), subtracting from it the average of the polish rate for the 4 outermost sites on the wafer (sites 6, 7, 8, and 9), and dividing by twice the mean polish rate for the wafer. This gives a nonuniformity measure from the center to the edge with a range of ±100%. The polish rate nonuniformity for a lot is the mean of the nonuniformities for the four data wafers in each lot:

$$NU_k = \left(\frac{\sum_{j=1}^{4} NU_{jk}}{4} \right);$$

$$NU_{jk} = \left(\frac{\left(P_{1jk} - \left(\frac{P_{6jk} + P_{7jk} + P_{8jk} + P_{9jk}}{4} \right) \right)}{2 \times \left(\frac{\sum_{i=1}^{9} P_{ijk}}{9} \right)} \right);$$

The six charts that show each of these measures for lots 1 through 9 follow*. Also shown in Table 9 are the settings used for polish time and back pressure for each lot. Note that the settings and results for lot #0, which supplied initial conditions for the RbR software, are not shown here since they were not obtained under RbR control.†

Lot #	Polish Time (seconds)	Back Pressure (psi)
1	136	1.9
2	146	2.6
3	154	2.8
4	131	3
5	125	3
6	123	3
7	135	3
8	121	3
9	121	3

Table 9: Settinngs Provided by RbR Controller

Before interpreting the data, the reader should note that I made a processing error on lot #4 in operating the software, which resulted in the RbR controller suggesting a spurious polish time of 131 seconds as shown. Operating the software correctly would have given a suggested polish time of 145 seconds, or 14 seconds longer than was actually used on

*I have converted polish rate data into a percentage of a nominal rate to protect DEC proprietary data.

†They were taken from the center point results of the just-completed response surface experiment, as described in the previous chapter.

lot #4. This does not invalidate any subsequent results, since the RbR algorithm does not use the history of its recipe suggestions in its calculations. However, when reading the four film thickness outcome charts, lot #4 should be discounted, while the polish rate data do remain meaningful.

Lot #4 is significant for another reason: it is here that the back pressure setting first reaches the allowable maximum 3.0 psi, where it remains for all further runs. This indicates that the machine state has drifted to the point where it can only be adequately compensated for by excessive application of back pressure. From this point on, the RbR algorithms have only one practically remaining control variable, polish time, so the best that can be expected from the software is that grand mean wafer thickness will stay close to 12.5 kÅ. That is, the ability to compensate for degrading variability has been lost after lot #4. This is a consequence of the physics of the CMP machine and of having only two control variables to begin with. Again, it is useful to segregate the results into those "before" and "after" lot #4.

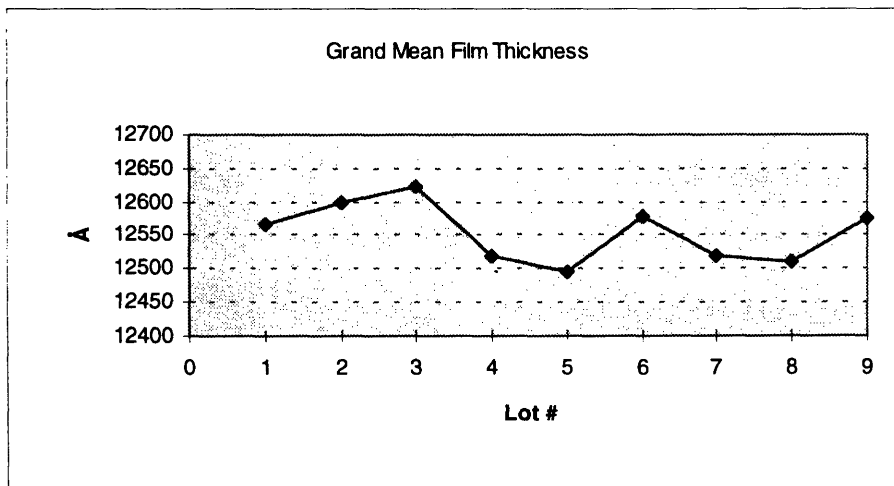

Figure 12: Grand Mean Film Thickness Results (TT_k)

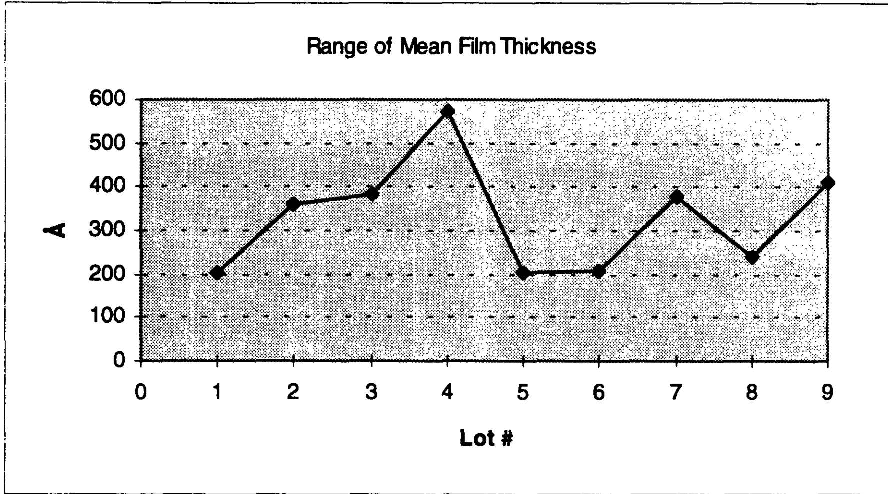

Figure 13: Range of Mean Within-Wafer Film Thicknesses (TR_k)

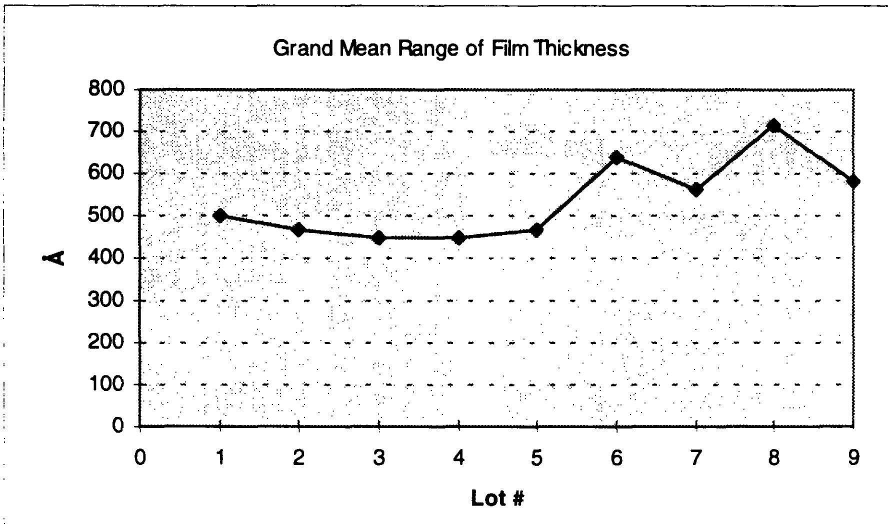

Figure 14: Grand Mean of Range of Film Thicknesses Across a Wafer (RT_k)

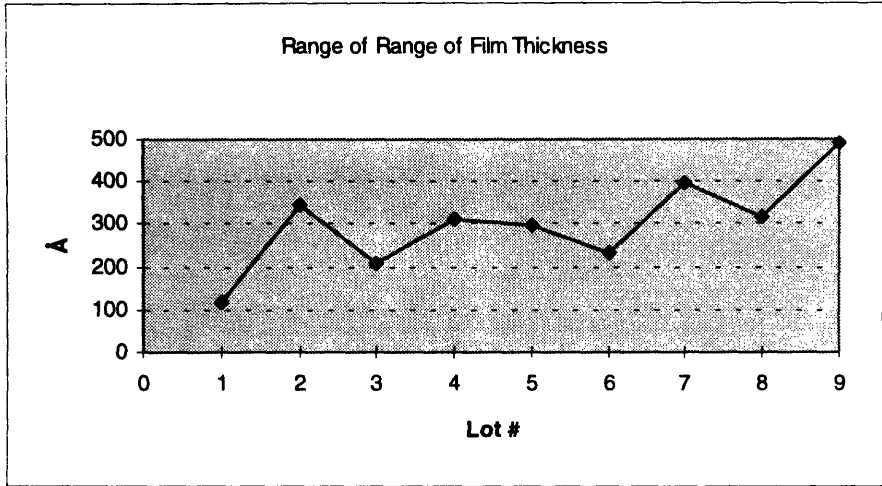

Figure 15: Range of Range of Film Thicknesses Across a Wafer (Rr_k)

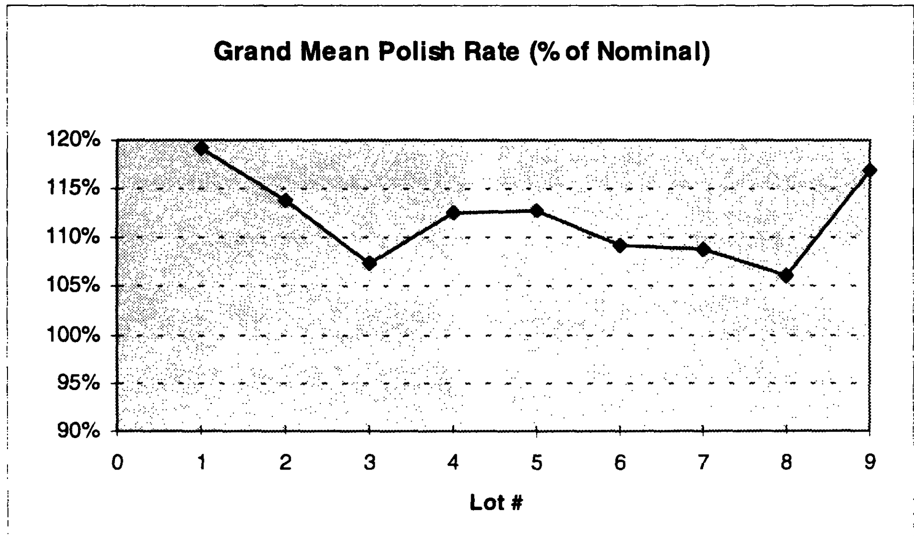

Figure 16: Grand Mean Polish Rate (P_k) as Percent of Nominal Rate

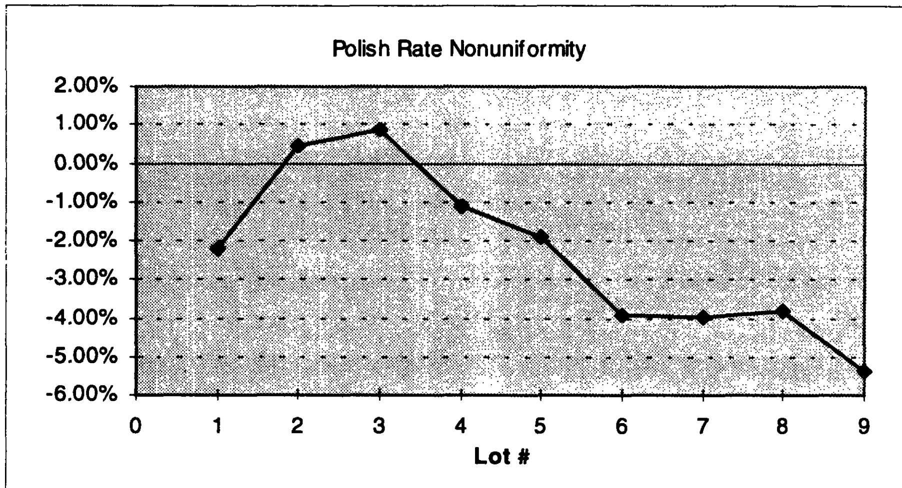

Figure 17: Polish Rate Nonuniformity (Nu_k)

Looking at the results obtained before and after the RbR controller "hits the wall" at lot #4, the controller seems to do a credible job of controlling average film thickness and film thickness variability as long as the state of the machine permits it to do so. Once it is down to one control variable, the mean film thickness remains within roughly the same band, but the various range measures steadily deteriorate as the machine continues to drift.

Meanwhile, the effective polish rate shows a steady decline (with the exception of the uptick on the last lot) consistent with intuitive expectations. It might be possible that back pressure could marginally raise the overall polish rate, but to a first approximation the RbR controller has no way to restore decaying <u>mean</u> polish rate; it can only try to compensate for worsening <u>uniformity</u> in that rate as experienced by a film on a wafer. The final chart most clearly shows the breakdown of polish rate variability control after lot #4.

Chapter 5: Economics of CMP as a Replacement for an Existing Planarization Process

The CMOS-5 fabrication process used by Digital Semiconductor to fabricate the 21164 Alpha microprocessor is a 4-metal-layer, 0.5µ process.[39] This process does not use CMP to planarize inter-metal dielectrics, but instead uses state-of-the-art local planarization techniques. It was proposed to introduce CMP planarization in the "back end" of the CMOS-5 process, that is, to polish one or more inter-level dielectric layers, to bring CMOS-5 in line with planarization technology trends[40] and improve its overall quality.

More concretely, the significant expected benefits of back-end CMP included higher probe yield via reduced defect density and a wider process window for photolithography. The global planarity achievable with CMP would also permit the back end process to be enhanced for better performance characteristics, for example, metal line geometries could be reduced further, which would mean smaller die sizes and therefore lower average die cost and improved die yields for Fab 4.[41] The question was whether introducing a new process technology to the CMOS-5 back end was "worth it."

This turns out to be a complicated question. For example, an important aspect of this complexity is the operating backdrop into which CMP was to be introduced into the back end of CMOS-5. CMOS-5 was a production-qualified process, not a new process under development. However, it was still relatively early in its life cycle, meaning the volume of wafers it processed was at its lifetime low, as was process yield. This was not a static situation: volume was being quickly increased ("ramped") and yields were improving as engineers, technicians, and operators learned more about the process. The fab was working hard to meet its near-term business commitments as well as its long-range capability plans. This was challenging enough to manage, so why place any of this at further risk by changing a process technology? Even "mundane" technology introductions

on the factory floor have a poor track record in practice: for instance, a study by Hayes and Clark found that "in most cases the additional cost, over several months, of adding new equipment (in terms of lost labor productivity, increased waste, equipment idle time, and so forth) appeared to be greater than the cost of the equipment itself."[42]

There was also a cultural component to the situation. In many high-technology businesses, the push for new technology often comes from the engineering staff, who focus on technical benefits. Aside from basic figures such as equipment prices and local installation charges, the task of calculating the net financial impact on the business is frequently passed over to financial analysts. The financial analysts then perform what are often viewed by the engineering culture as a series of mysterious computations that generate a number, such as the return on investment (ROI). If the ROI is high, then the engineers accept their good fortune and move on, while a low ROI forces the engineers to find other benefits ignored by ROI, such as "strategic considerations," or to give up; the unvoiced opinion often is that "bean counters" have erected a roadblock to "doing the right thing." (Kaplan[43] provides an accounting perspective on this issue.) The engineers and financial analysts lack a common language to permit decisions to be made with a minimum of confusion and frustration over which side "won."

There are at least two sub-problems here: (1) engineers' insufficient understanding of the financial calculations and why/whether/when they are meaningful, and (2) engineers and financial analysts not translating "strategic considerations" into dollars, thereby undervaluing certain projects. Originally, I was presented the "is it worth it?" question by my first internship supervisor primarily as an exercise in cost of ownership[44] (COO) calculations. By exhaustively and uniformly accounting for every cost driver that impacts the acquisition, installation, operation, and maintenance of capital equipment, COO provides a systematic methodology for factories to make a variety of comparisons amongst competing machines and technologies. But, while calculating the cost of ownership would have been one possible way to bridge the first gap, it would not have dealt with the second, nor with the other sources of complexity previously mentioned.

5.1 Analysis Approach

To deal with this question and its ramifications, I used an analysis approach that had the following (often overlapping) components:

- *I adopted net present value (NPV) as a common decision guide.*

  An investment's NPV is the monetary value today of the expected future cash flows generated by the investment, less the investment's cost. The farther out in the future and the riskier a revenue stream is, the less it is worth in NPV terms. The advantages of focusing on NPV were: (1) many aspects of the "is it worth it?" question could be translated into NPV, (2) NPV is cash dollars, i.e., it is not a cost accounting abstraction that engineers can simply dismiss as "funny money," and (3) NPV is the best financial decision metric[45] because it rates a project on whether it will increase the company's value. Therefore, NPV was general and powerful enough to provide a common language as well as a common decision metric for engineers, managers, and financial analysts.

- *I applied a structured framework to deal with the complexity of the problem.*

  A sufficiently general framework was missing which could (1) permit the complexity of the problem to be systematically and coherently addressed, while (2) providing a more powerful lens for viewing the proposal than that afforded by COO alone. I believe it was the absence of a suitable analysis framework that explained why management was still wrestling with the economics of back-end CMP when I arrived, months after the engineering development work on it had begun.

- *I focused on illuminating relevant issues more than on generating a final number, and made assumptions, contingencies, and options explicit in the decision framework.*

  It seemed to me that the most fruitful path to analyzing the situation would avoid a black box approach and expose effects of a variety of drivers on the end result. Unless people understood when and why the NPV results might change significantly, they could not be expected to buy into the decisions implied by those calculations. I chose to put the analysis framework in spreadsheet format to facilitate sensitivity analysis; the idea was to allow people to explore the space of parameter values that give a

positive project NPV and understand the robustness of various outcomes on their own.

This analysis approach led me to develop a particular decision framework for evaluating whether and when it might be justified to replace the existing planarization technology with CMP in the back end. The remainder of the chapter will consist of a walk through that framework. Any and all numeric data used will be strictly illustrative, and do not represent actual measures of the CMOS-5 process, the Fab 4 facility at Digital Semiconductor, or any other aspects of the DS business. For simplicity, all dollar figures cited are without inflation. Keeping DEC's recent large operating losses in mind, I also assumed a 0% effective annual tax rate, since DEC can "carry forward" much of these losses into future years. (One effect of this is that I assume no tax shield benefits to DEC from capital depreciation of purchased equipment like CMP machines.)

5.2 Decision Framework

The decision framework poses numerous questions about the proposal and tries to answer them in NPV terms. While using the framework, a variety of assumptions about manufacturing strategy, including the technology roadmap of the business, the production volume plan, and the marketing plan, must implicitly be made and applied. I will not specify what these assumptions were at DEC; suffice it to say that a fab that is competing, for instance, on fast cycle time will look at these questions differently from one that is competing on low cost production.[46] The top-most level of the decision framework consists of three categories: Cheaper, Faster, and Better.

5.2.1 Cheaper?

Some key elements of COO calculations are germane to this question, including the relative price tags of the equipment (with installation charges), the annual material and labor cost expended to operate them, and the amount of equipment needed to attain the desired capacity levels at the desired times. Since Fab 4 is already using CMP equipment in the CMOS-5 process, it is able to estimate capacity, labor, and material needs for the back end with more assurance than if it was a neophyte CMP user. This is particularly

important considering that capacity, i.e., processing speed per machine, drives the basic capital acquisition requirement for the fab:

$$\left\lfloor \frac{N \times Capacity}{F} \right\rfloor = 1$$

where N is the number of machines required of a given technology, and F is the target throughput capacity of the fab. The conversion of capital cost, labor and materials to NPV terms is straightforward.

5.2.2 Faster?

The existing planarization technology uses a number of processing steps on several machines in the fab. For each of these steps, a cassette of wafers enters a queue, is processed, may be measured, and is transported to the next step. In assessing relative processing speeds of CMP vs. the existing technology, one can consider the "static" cycle time, which refers to the processing time only, and the "dynamic" cycle time, which is the total time an actual cassette takes on average to move from one operation to another in the fab. While the processing time of each of the above steps is small relative to CMP (for instance, a film deposition is a batch operation on the entire cassette at once), taken together, the static time to planarize a wafer the current way may not be much different from CMP static cycle time. The significant difference may be in dynamic cycle time: having to stand in one queue (for CMP) instead of many queues with many transport steps means that CMP will exhibit less dynamic variability, and therefore will have the shorter dynamic cycle time assuming roughly comparable static cycle times.

The question is, does any of this impact either the fab cycle time, which is the time the fab takes to turn a raw silicon wafer into product, or the fab throughput, the rate at which the fab produces product? The answer depends on the operating context in which the technology is to be inserted, and specifically on which operation is the bottleneck operation limiting the fab's throughput.[47] If and only if back-end planarization is the current bottleneck, and/or inserting CMP would make it the bottleneck, will these cycle time considerations impact fab throughput. In such a case, it would be extremely useful to supplement a paper estimate of the net change in throughput with that produced by a

validated dynamic simulator. (For instance, Wood[48] has developed a simulator that integrates economic and technological information in assessing various fab designs.) For this exercise, I assume that in fact the fab's throughput bottleneck is elsewhere, and that CMP will not become the bottleneck if it is deployed.

The fab cycle time will be impacted by the introduction of CMP, with its reduced dynamic variability as described earlier. But is the cycle time impact *significant?* Qualitatively, cycle time reduction has been credited in the literature with improving learning rates and reducing defectivity, thereby improving yield. Unfortunately, recent studies have been thus far unable to statistically validate this belief in a causal relationship between shorter cycle time and higher probe yield.[49] Nevertheless even if we accept this assertion based on engineering judgement* it seems likely that new *plateaus* of cycle time performance must be reached to produce significant yield impact. It will be difficult to know in advance whether such a plateau is reached, if ever. Instead, I focus on the fact that shorter cycle time also reduces work-in-process (WIP) inventory, and hence WIP carrying costs. In this case every increment of cycle time saved is equally valuable. With this in mind, I concentrate on WIP carrying costs to assess the cycle time reduction benefit of CMP.

Little's Law[50] provides a rough estimate of the effect of reduced cycle time on WIP, assuming the fab is running at its throughput capacity:

$$\Delta L = \lambda \times \Delta W$$

i.e., the change in WIP (ΔL) is the fab throughput rate (λ) times the change in cycle time (ΔW). WIP represents working capital that is being invested to keep production going at a certain rate. If this capital were not being used here, it could be invested somewhere else in the business and earn the rate of return for the business. Thus putting working capital into WIP has an *opportunity cost* that is the foregone income from not investing

*Or faith!

elsewhere in the business. The opportunity cost of WIP is its carrying cost times the opportunity cost of capital for the business:

$O = \Delta L \times CarryingCost \times r$

From this, we see that as fab throughput rates increase, and as the average selling value of a wafer in the manufacturing line increases, a given cycle time improvement will be much more valuable. Also, the more expensive capital is, the higher the opportunity cost paid by the business for tieing up working capital in WIP.

However, as Wood[51] points out, this dollar incentive for reducing WIP must be balanced against maintaining the minimum fab loading needed to keep the bottleneck processes fully busy; if total WIP drops below this threshold it will reduce fab throughput and therefore increase the average cost per wafer. For the purposes of this analysis I assume that we remain above this threshold.

To get a sense of the dollar savings, for a 5000 wafer starts per week (WSPW) fab, a 1 week cycle time reduction would reduce WIP by 5000 wafers. Assuming carrying cost per wafer of WIP to be $1000, this represents $5M of savings that could be invested elsewhere in the business. Using the average historical semiconductor industry opportunity cost of capital of 15%[52], the opportunity cost savings for 1 year would be $750K.

5.2.3 Better?

Whether or not applying CMP technology to back-end planarization will be "better" than staying with the existing method is itself a multi-faceted question that can be addressed by breaking it down into component questions about core competency, process yield, disruption effects, and new options and contingencies.

5.2.3.1 Core Competency

A classical benefit of implementing a new technology is to provide a learning platform that would otherwise have to be built by the next technology generation. The argument would go, "We know we'll need back-end CMP in future manufacturing processes, so we

should begin going down the learning curve on this technology today, otherwise we'll be starting from scratch years from now." (Recent empirical research[53] on the production of EPROM semiconductor memories also supports the hypothesis that an incumbent technology user has an advantage over a new entrant.) A related rationale argues that manufacturers should be open to developing new capabilities or core competencies that will help take them in the competitive direction indicated by their business strategy.[54]

However, Digital Semiconductor has employed an aggressive technology development method that ensures minimal time-to-market, using dual overlapping development teams.[55] The practical effect of this method is that back-end CMP is already being considered for the next-generation technology, so that even if CMOS-5 engineers don't learn about back-end CMP now, Digital Semiconductor as an organization may still be going down the learning curve. The difference will be in a slower net rate of learning than if two teams were attacking the problem. Nevertheless, the degree to which this proposal improves the firm's strategic flexibility by *virtue of acquiring a new core competence* seems limited here, and will not be considered further.

5.2.3.2 Yield

Probably the most elemental facet of introducing a new process technology such as CMP is the perceived opportunity to increase process yield. From an engineering perspective, CMP, by providing complete planarization, can remove defect modalities that arise in processing because of a relative lack of planarity. CMP may even excise defects that would have been caused by embedded particles by literally polishing them away. Yield may also improve because of a wider process window for photolithography, or the overall back-end process, once integrated with CMP, may be simpler or otherwise less defect-prone. Of course, CMP also comes with its own set of operational and process challenges that can negatively affect yield, for instance, debris generated by polishing can be a potent source of particle contamination of the wafer. Fundamentally, however, there is an expectation that overall yield will be improved by introducing CMP.

Economic Benefits

Assessing the economic benefit of improved yield can proceed with a cost or revenue-oriented viewpoint, and starts with the average number of good die on a processed wafer, referred to at Digital as the equivalent quantity shipped, or EQS. EQS is the product of the number of die per wafer, the fab's line yield, die probe yield, assembly yield, and the yields of all subsequent electrical and functional tests. The EQS tells how much throughput is needed to satisfy product demand; summing this over all products gives the total required (not necessarily actual) fab capacity:

$EQS_i \times WSPW_i = Demand_i$ for each product i, and $\sum_i Demand_i = Capacity_Needed$

For a given demand level, increasing EQS will permit sufficient product quantities to be made with fewer wafer starts. So the value of improved yield can be assessed by determining the cost savings of less required capacity. This can be done by accounting for the cost of making scrap.

For a given increase in EQS, we have (for a given product demand):

$$EQS \times WSPW = (EQS + \Delta EQS) \times (WSPW - \Delta WSPW)$$

which simplifies to:

$$\frac{\Delta WSPW}{WSPW - \Delta WSPW} = \frac{\Delta EQS}{EQS}$$

CMP is expected to impact die probe (functional) yield, primarily, as opposed to line yield, or downstream parametric test yields. Also, a given product has a predetermined number of die per wafer. This means that:

$$\frac{\Delta Yield_{probe}}{Yield_{probe}} = \frac{\Delta EQS}{EQS}$$

The value of improving EQS is represented in these equations by it ability to reduce the production rate (WSPW) needed to satisfy product demand. If EQS is small to begin

with, a modest improvement will have a large impact, but for a high baseline yield performance the same yield improvement will not give as much economic benefit.

This can also be seen if, as stated above, we account for yield improvement benefits by figuring the cost of making scrap. This can be done either by assessing this cost to the reported cost per die, or by costing die as if the yield was 100% and treating scrap costs as a separate expense. Either way, the total cost should come out the same; I choose to use the former method because the formula is brief:

$$C_{scrap} = \left(\frac{WaferCost}{EQS} - \frac{WaferCost}{EQS + \Delta EQS} \right) \times Demand$$
$$= \left(\frac{\Delta EQS}{EQS + \Delta EQS} \right) \times WaferCost \times Demand$$

Again, where EQS is low, a given improvement in yield can substantially reduce the incurred cost of scrap. The basic message of these equations seems to be to perform yield-improvement investments as early as possible in the fab's life cycle, when the product of per-wafer costs and demand is relatively high and yields are relatively poor.

On another front, increasing EQS will permit proportionally more product revenue to be generated per wafer. This is because each "extra" die that is yielded can be packaged, tested, and sold. Assuming the marginal costs of packaging, testing, and so on do not exceed the marginal revenue obtainable from selling one more chip, then the resulting net revenue should be counted towards the financial benefits of higher yield. (Either demand exceeds supply at the market price, in which case the fab can sell every "extra" chip it makes at a given wafer production rate with higher yield, or demand is already met at the current levels, in which case the fab can switch part of its capacity to another product. If increased yield would only create piles of unsold inventory, there are fundamental business problems that are beyond the scope of CMP technology to address.)

In contrast to the cost of scrap, the revenue benefit of improved yield is insensitive to the baseline yield; it is just the product of the incremental income per good die and ΔEQS. Qualitatively, this can be a much larger number than the reduced cost of scrap, so to ignore it may significantly undervalue the value of improved yield to the business. Yet it is also sensitive to the vagaries of market pricing, and therefore adds another element of uncertainty to the assessment. It also pulls the focus of the analysis further from a purely factory-based view.

For the purposes of this analysis, I chose to consider yield-driven revenue improvement alone because it is consistent with the financial, cash-flow view of NPV, and because it is lilely to be much greater than the cost of scrap; had the context been more oriented to cost accounting, I would have used the cost of scrap.

Yield Modeling

Over the years, the semiconductor industry has developed sophisticated yield models for predicting EQS. Yield models are generally a function of the average number of defects per unit area and of the area of the chip in question, and are usually empirically developed by each factory to drive continuous improvement, assess the manufacturing costs of proposed products, and otherwise assist operational decision-making.[56] A well-known model, which I will use here for illustrative purposes, is the negative binomial:

$$Y = Y_i \times \left(1 + \frac{D_0 \times A}{\alpha}\right)^{-\alpha}$$

where D_0 is the defect density, A is the chip area, and α is the "cluster parameter". α is often between 1 and 3 for logic chips like microprocessors; I select $\alpha = 2$ for convenience. Here Y is the product of the line yield Y_l and the probe yield, which is the yield of electrically good die at wafer test or sort. Line yield for the fab accounts for grossly misprocessed, e.g., broken, wafers. (We might anticipate that the multi-step planarization process in current use would present more mis-processing opportunities than the single-machine CMP technology.)

The utility of this modeling approach is that it focuses process improvement effort on the myriad physical anomalies — defects — that can cause incorrect electrical behavior, i.e., that directly drive measured yield results. It also acts as a gross reflection of the degree of process control at a given point in time: presumably, tightly controlled processes will have low defect densities. (This is the economic argument for trying run-by-run process control of CMP.) However, it is only a snapshot in time of the process. How quickly defect density is reduced over the lifetime of of the fab is not comprehended by this modeling method. In the following discussions of disruption and of options and contingencies, I will bring in the important element of time.

5.2.3.3 Disruption

In manufacturing, technology retrofit decisions are often not entertained at all, on the principle that once a process is "qualified" for production it is simply too disruptive to consider technological modifications. The onus is placed on the process developers to anticipate technology trends and plan for their smooth introduction over successive technology "generations." Research on new process development[57] also supports separating process development from production *per se*; the semiconductor industry has seen the rise of the "pilot fab" that is dedicated to prototyping new manufacturing processes. However, consider once again the situation in Digital Semiconductor's Fab 4:

- The CMOS-5 process has only been production qualified relatively recently;
- Fab 4 is the development fab for CMOS-5, and is becoming the first production fab for CMOS-5;
- DS is a small operation by merchant semiconductor industry standards, with only one or two other fabs to which the 0.5 micron process could be promulgated;
- Fab 4 is already using CMP in another portion of CMOS-5, so its incremental cost of learning to apply CMP to interlevel dielectric planarization is lower than if CMP was being introduced from scratch.

So the CMOS-5 process is still a relatively new process, and the scope and span of the process knowledge transfer problem is limited: perhaps the back-end CMP proposal is not *prima facie* too late and/or too ambitious to succeed.

On the other hand, qualitative research by Bohn[58] warns of the substantial management challenges to successful learning in an environment such as Fab 4, which is trying to ramp up production. A recent empirical study, also by Bohn,[59] shows that a high degree of process variation (noise) can be present even in a "high volume" production fab, and in fact this noise can make it surprisingly challenging to manage the yield improvement process in a given plant. For instance, Bohn observed that the chance that an experiment on a process change that gave a true yield improvement of 3% — substantial impact for a single change to a complex manufacturing process such as CMOS VLSI — would give results that would lead the engineers to *reject* the change, ranged anywhere from 18% to 40%! This reinforces the need for sophisticated management of the yield enhancement / learning process.

None of the fabs measured by Bohn was reported to be altering its basic process technology, but this is what we propose to do with back-end CMP. While the end resulting yields might be better, the above research should raise doubts about just how and when those end results may be achieved. In fact, the track record for factory floor process technology changes has not been good, as was noted earlier. Chew et al.[60] in particular report a qualitative model of what I will refer to as the cost of disruption, which is the anticipated loss of fab revenues due to production delays and interruptions as new technology is introduced. This goes beyond the planned cost of the development effort needed to put the new technology into production, and reflects the realities of machine downtime, immature maintenance processes, and so on. It probably does not reflect the "opportunity cost" of having engineers and others work on the new technology instead of continuing to improve the old. I have roughly redrawn their figure, "Murphy's Curve," in Figure 18.

Murphy's Curve implies that the "hit" to yield by introducing and then coping with new process technology is early and substantial, and that it may take a significant amount of

time to beat back process noise to levels where systematically effective learning (e.g., few Type II errors of the sort noted by Bohn) is driving yield enhancement.

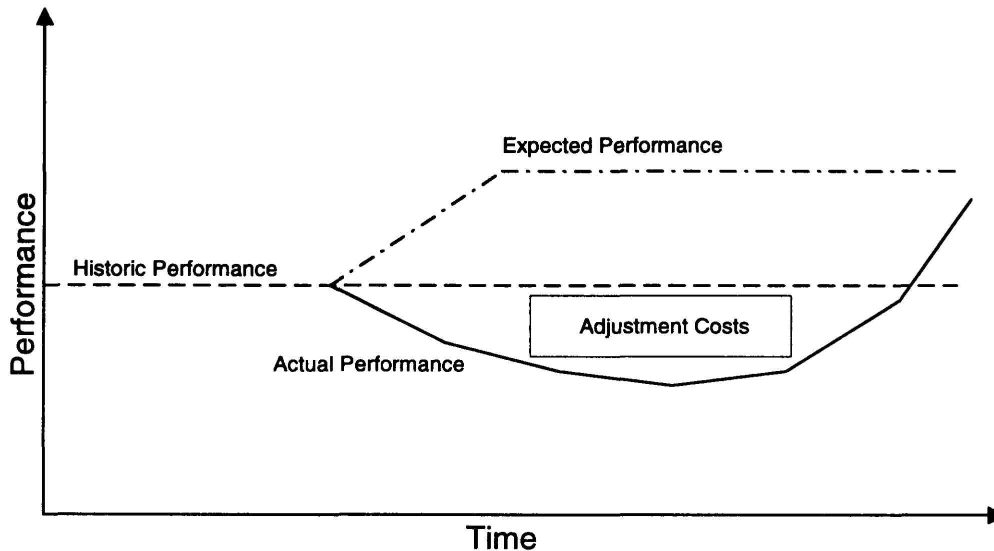

Figure 18: Disruption Costs of New Technology Introduction

In assessing comparative fab performance, U.C. Berkeley's Competitive Semiconductor Manufacturing Program researchers recently developed a statistical model of yield improvement against a number of manufacturing variables.[61] This was based on data from over 30 fabs in the United States and overseas. For a given fab in the Berkeley study, the yield improvement regression model was:

$$W = \alpha_0 + \alpha_1 \cdot DieSize + \alpha_2 \cdot \log(P)$$

where P is the process age and W is a transformation of die yield:

$$W = \log\left(\frac{y}{1-y}\right).$$

The W transformation reflects the common experience that the difficulty of obtaining the next incremental yield improvement increases as overall yield rises. Looking at a specific fab, the first two terms in the regression form a baseline yield, while the last term describes how quickly the fab has improved yield on average over time; α_2 is the fab's "learning rate." Fab 4 possessed its own projections for baseline yield and yield

improvement, for each product (die size), over the next few years. Fitting these projections to the Berkeley model, one could impute the expected Fab 4 "learning rate."

To model the disruption costs of introducing CMP, I had the following considerations. First, there is no analytic or simulation model described in the research literature that predicts the amount of disruption to be experienced; there is no model of the performance/time curve as a function of measured disruption drivers. Developing such a model was well beyond the scope of this work. Second, at the other extreme, there is little benefit to merely positing a total disruption cost and entering that number into the net present value calculation. Such a black box technique provides no insight and is pure guesswork. Third, although I initially tried perturbing Fab 4's α_2 to model the disruption in learning, this implies a steady, long-range effect that contrasts with the deep short-run effects observed by Chew et al.

Therefore, I choose to model yield (including the cost of disruption) as follows:

1. I set a starting yield point corresponding to the current process defect density with the current planarization technology, and then transform it to W;
2. I extrapolate a W line for the current planarization technology based on the Fab 4 learning rate. If CMP yield falls below this line (<u>not</u> the horizontal) then a disruption cost is incurred, while falling above this line indicates that CMP is giving a net yield benefit;
3. I posit some percentage improvement in defect density due to CMP technology (roughly speaking, the positive "bump" one might expect due purely to theoretical engineering considerations);
4. I use the ending yield from (2) along with the CMP defect density from (3) and the negative binomial model to get an ending CMP yield, which I transform to W;
5. I model the CMP W vs. time relation as a concave-shaped group of three connected lines, using the starting W from (1) and the ending W from (4) as two of its four points;

6. I posit the location of the third point and fourth points by making assumptions about how deeply and quickly yield will dip, and then how quickly it will recover. This allows various "disruption scenarios" to be played out, even if I can't predict whether any one of them will occur.
7. I transform W back to yield, and into net revenue impact, to obtain an input to the overall net present value calculation.

The resulting model has the basic form shown in the following figure.

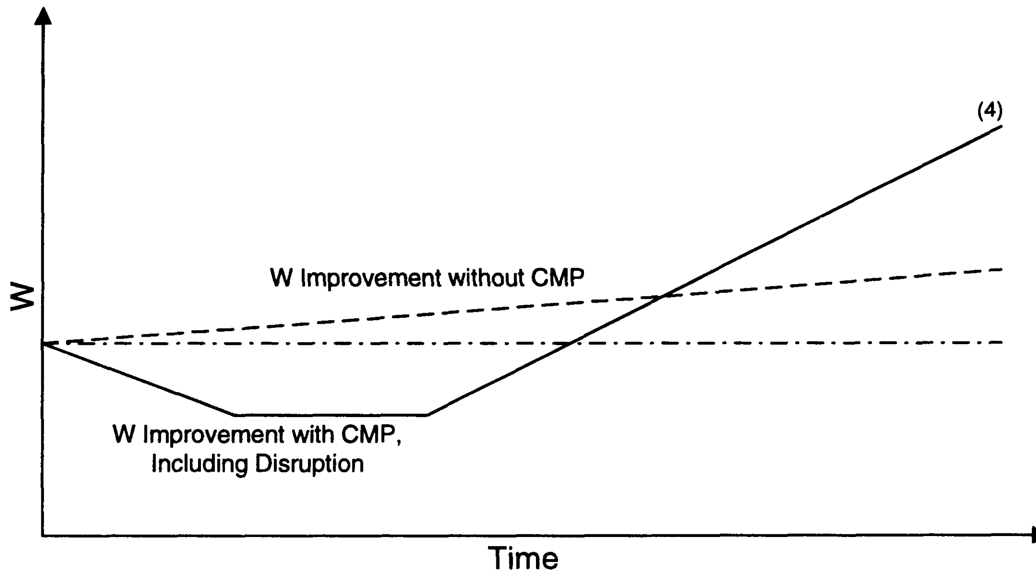

Figure 19: W Improvement vs. Time

This model implies that, for the introduction of a new process technology like CMP to succeed, the immediate effects of disruption need to be minimized, and that recovery from disruption should proceed, on average, faster than the historical fab learning rate, in order to be able to achieve a net benefit from the new technology. This reinforces the observation by Chew et al. of the importance of shrewdly managing new technology introductions on the plant floor:

> "...managers typically underinvest in learning both before and after startup. This is particularly true of the organizational changes relating to new technologies. To correct these deficiencies, firms must radically alter the way they think about and plan the implementation of technology."[62]

To demonstrate the model, I will use the following contrived scenario:

- The time line is 5 years from (1) to (5);
- Starting probe yield of 50%, and constant line yield of 95%;
- CMP improves total process defect density by 20%, i.e., $D_{CMP} = 0.8D_0$;
- The maximum yield disruption is 10% of the starting probe yield, occuring 3 months after (1) and lasting another 3 months before starting to recover;
- The learning rate for the fab is the industry average = 0.35 reported in the Berkeley study.

With these numbers it is possible to calculate a net present value effect for adopting CMP that reflects process yield impacts on revenue. An example calculation is shown in Exhibit 1, which compares the NPV of the income stream from products manufactured with the current process to that from products manufactured during a switch to CMP in the back end. In addition to the assumptions already described above, I fabricated data on fab throughput, income per chip, and the number of chips per wafer that is intended to suggest the situation of a fab ramping production volume with a new process, and a profitable new product line.

In this case, the effects of disruption continue to be felt long after the yield dip in the first year, despite the fact that eventually the technical yield benefits of CMP are realized (84% vs. 81% without CMP.) This is evident in the continued yield lag in years 2 - 4. For CMP to have come out ahead in this scenario would have required a much shorter yield crash at the beginning, followed by a "burst" of yield learning, to permit CMP yields to catch up by year 2 or 3.

So far, time has been considered in the context of changing yield performance. The next section looks at how the proposed introduction of CMP also impacts the time component of managerial decision making, by adding new options and contingencies.

	Year 1	Year 2	Year 3	Year 4	Year 5
Fab Throughput (WSPW)	1000	2000	4000	4000	4000
Income Per Chip	25	25	20	15	15
Chips per Wafer	200	200	200	200	200
YIELD MODEL					
Starting Probe Yield (1)	50%				
Ending W	1.43				
Ending Yield	81%				
Learning Rate (α2)	0.35				
Avg. Process Age (Months)	6	18	30	42	54
Average W	0.627115814	1.011630115	1.190419084	1.308184366	1.396144416
Probe Yield	65%	73%	77%	79%	80%
Line Yield	95%	95%	95%	95%	95%
Current EQS	124	139	146	150	152
Income	$ 161,003,293	$ 362,269,488	$ 606,091,373	$ 466,657,600	$ 475,171,498
NPV of Income	**$ 1,315,502,770**				
YIELD MODEL: CMP					
% Improvement in D0	20%				
% Max Yield Disruption	10%				
Ending Yield	84%				
Ending W	1.67				
	Year 1				
	Q1	**Q2**	**Q3**	**Q4**	
Average W	-0.100335348	-0.200670695	-0.148793452	-0.045038966	
Probe Yield	47%	45%	46%	49%	
EQS	90	86	88	93	
Income	$ 29,327,371	$ 27,787,500	$ 28,582,230	$ 30,179,828	
		Year 2	**Year 3**	**Year 4**	**Year 5**
Average W		0.214347249	0.629365193	1.044383137	1.459401081
Probe Yield		55%	65%	74%	81%
EQS		105	124	141	154
Income		$ 273,370,995	$ 515,613,889	$ 438,491,107	$ 481,022,257
NPV of Income	**$ 1,141,807,575**				

Exhibit 1: Comparison of Yield Effects on NPV of Income

5.2.3.4 Options and Contingencies

Until now the analysis has focused on "passive" cash-flow benefits. This leaves out the fact that investing in CMP technology for the back end of the CMOS-5 process gives fab management an option on real assets[63, 64]. This option, like options on financial assets such as common stocks, has a monetary value, and therefore to ignore it would be to undervalue CMP, perhaps significantly. However, just as it is necessary to consider the capital cost of CMP equipment versus the capital that would otherwise be expended if CMP were not chosen, it is necessary to weigh the option CMP provides against the options already provided by the existing planarization technology (and which would be forfeited if CMP were adopted.)

There are two separate options to be considered in the case of back end CMP, one for the near term and one for the future. The near-term choice is to reduce the dimensions of the upper-level metal lines. Microprocessor Report[65] lists the contacted pitch of the third-level metal for CMOS-5 as 5 microns, the largest it reported from among major CMOS vendors such as Motorola, Intel, and Texas Instruments. Fab 4 management has the option to shrink these dimensions if it so chooses. The customer benefit would be quite visible, compared to other manufacturing process technology changes that are often undertaken: cutting the minimum achievable die size for a given VLSI design.* Smaller chip size means less cost per die, which can be used to increase fab market share and profitability.

This process enhancement can be undertaken with either the existing planarization technology or with CMP as a starting point. The global planarization provided by CMP, however, means that the metal lines can be shrunk and squeezed together more aggressively; the minimum achievable metal line spacing with CMP could be expected to be about half that without CMP, absent inter-level metal connection architecture changes.

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*CAD routing algorithms will differ in their ability to take advantage of tighter design rules; for simplicity assume the same CAD tools are used throughout.

The superior planarity afforded by CMP also better enables such techniques as stacked vias, which permit software routers to pack circuits even more tightly.

I use a decision tree (shown in Figure 20) to consider this question in NPV terms, by calculating the expected value of the NPV, given each possible decision: the decision that maximizes expected NPV is the "best" choice. In this case, the decision is whether or not to adopt CMP. Once that decision is made, three scenarios can arise:

- Market conditions dictate a "modest" metal line shrink, i.e., one that can be accomplished without the added planarity provided by CMP (with probability p2);
- An "aggressive" shrink is needed that requires CMP (with probability p1);
- No shrink is needed.

If CMP is adopted, then the first two scenarios will have the same effect (p = p1 + p2), which is that some nominal engineering cost ($1M, for illustration) will be incurred to implement the shrink, so the NPV of the project is just the NPV of doing CMP, less $1M. If no shrink is needed, the NPV is the NPV of doing CMP.

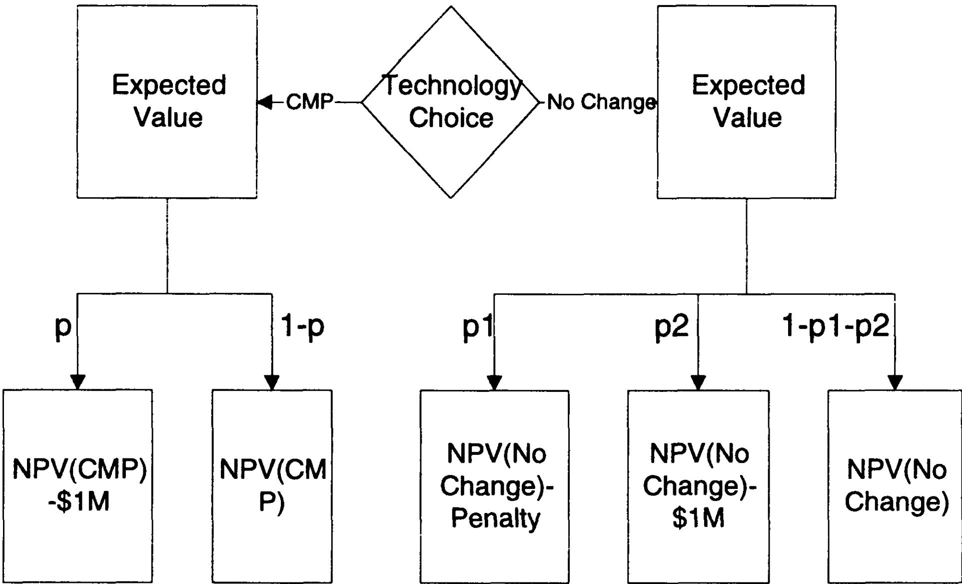

Figure 20: Decision Tree to Shrink Upper-Level Metal Lines

If we stay with the current planarization technology, and a modest shrink is needed, we reduce the NPV by $1M, compared to the NPV of not changing to CMP. Similarly, if no shrink is needed, the NPV doesn't change. However, if it is the case that the market demands an aggressive shrink, then we will be forced to adopt CMP later, or to forfeit market share. Since it is quite probable that once CMP has been foregone, that it is unlikely to be reconsidered, I assume the outcome is reduced sales. This is illustrated on the p1 branch of the decision tree by assessing a penalty to NPV(No Change).

Therefore the expected NPV of the CMP decision is:

$$E(NPV_{CMP}) = (1 - p1 - p2) \times NPV_{CMP} + (p1 + p2) \times (NPV_{CMP} - \$1M)$$

and the NPV of the decision to stay with current planarization technology is:

$$E(NPV_{NoChange}) = (1 - p1 - p2) \times NPV_{NoChange} + p1 \times (NPV_{NoChange} - Penalty) + p2 \times (NPV_{NoChange} - \$1M)$$

Once the NPV for no change and for CMP are determined via the calculations and considerations described in the rest of this chapter, and some estimation (or set of estimations) of p1 and p2 and the lost sales penalty are made, then the expected NPV values can be calculated. In practice, this determination requires considerable market research, and must be attuned with the overall business strategy of the fab and the firm.

Next, I consider the future option that I mentioned earlier, made possible by CMP. This option can extend the lifetime of the fab if it is exercised. *If CMP is used to planarize all three dielectric layers above the transistors, it makes possible a full-blown shrink of the entire process to a critical dimension of less than 0.5 microns.* Without CMP, such an option is not available to management.

This option is only available until such time as the planned next-generation technology arrives on the scene in volume. (Critical dimensions then would be even smaller than could be attained by this CMOS-5 process shrink I am discussing here.) The fast pace of industry CMOS technology trends does not make for a very large window, but there is a window, nevertheless, that could be exploited.

The same techniques Wall Street uses to value financial options can be used to value this option. Here, investing in CMP buys a call option on a real asset. That asset is the cash flows from a fab running this CMOS-5-Shrink process, for some number of years, over some product line, a few years from now. The option's expiration date is the last day when there is enough time to design and implement the shrink in the fab, and still capture the maximum available market before the future planned process kicks in. Just what those future cash flows will be is highly uncertain, but this actually makes the option more valuable, all other things being equal.[66] Finally, the option's exercise price is the process shrink development cost. Standard valuation methods, such as the Black-Scholes equation[67] can then be applied to give a net present value for the option to shrink the process. The power of this approach is that it transforms a "soft, strategic" consideration into a "hard, financial" consideration possessing a real NPV.

To illustrate, I assume that the shrink would boost cash flows by C = \$25M per year over a four-year period T, beginning two years after the decision is made. (The two years would cover time for R&D and factory deployment.) I assume that I have one year left to decide before the option to do the shrink expires. Using the 15% discount rate, these cash flows form an asset whose value will be, using the present value formula:

$$= \frac{\$25M}{(1.15)^{(2+1)}} \times \left(\frac{1}{.15} - \frac{1}{.15(.15)^4} \right) \approx \$47M .$$

I further assume that those cash flows could vary with a standard deviation of 40%, and that it will cost \$25M in engineering, capital equipment, and other considerations to implement the shrink. Using the Black-Scholes tables provided by Brealey and Myers[68] I obtain a ratio of option value to asset value of 0.47, so that the value of the option to shrink is $\approx 0.47 \times \$47M \approx \$22M$. This value should be counted in the overall net present value of implementing CMP in the back end.

5.3 Summary

By taking advantage of the fact that net present values are additive, the various NPV components of capital equipment cost, cycle time reduction, yield enhancement, disruption costs, and options can be combined into an NPV for the CMP project. The overall framework could apply to any proposed technology insertion, not just CMP. However, the real advantage lies not in generating "the" NPV for the proposal; there are many areas where absence of marketing data, validated models, etc., forces judgement calls to be made. Rather, the advantage of this framework lies in: (1) managing the complexity of the problem by structuring the analysis, and (2) enabling spreadsheet "what-if" exercises to test the sensitivity of the NPV outcomes to a variety of assumptions and perturbations.

Chapter 6: Conclusions

6.1 Design for Run-by-Run Control

As Hardt[69] points out, statistical design of experiments, statistical process control, and real-time feedback control represent a progession of process control techniques. The goal in DOE is to find the combination of settings for parameters that together give the "best" process response. The intent is to not change these optimal settings once they have been found, and in the case of Taguchi-style designs, part of their optimality lies in giving process responses that are fairly impervious to "noise," such as variations in those parameter settings. In statistical process control, when the process goes out of control, some exogenous root cause is to be identified and remedied to bring the process back in control; the process parameter settings are not altered. Only feedback control adjusts the process parameter settings to minimize process response deviations from target; the "optimal" setting constantly changes.

Selecting a control regime for a process is a fundamental part of process design. For instance, to perform Taguchi-style robust process design is *de facto* to plan to control that process in the factory via statistical process control. It is certainly the case that a real-world manufacturing process often has many process control methods active at once, for example, the servo control of the CMP wafer carrier rotational rate occurs along with SPC of the overall polish rate. But this is the result of subdividing the system into separate design areas of concern; within those areas there is a single control method, determined by the design.

From this perspective, simply walking up to an operating manufacturing process and applying a process control technique for which it was not designed is certainly risky, and probably doomed to failure. Sung-Do Ha's Ph.D. thesis demonstrated this point in introducing a new method for categorizing and applying process variabilities to improve

control. But this was, in retrospect, what I tried to do in my test of run-by-run control. For the front end CMP process, back pressure was not considered in the process recipe design, and so would be viewed as an extraneous noise source to be withstood. As it turned out, the recipe was highly robust to this unanticipated source of response variation. In the back end CMP case, the response to changing back pressure was significant, but insufficient to permit full-range compensation for drifting polish rate uniformity. *Neither process was designed to be controlled by run-by-run methods.* That is, the particular recipes being used for CMP were designed to work in a control regime other than RbR.

Process design for run-by-run control would still characterize the response surface using design of experiments, for each response to be controlled. But now the goal would be to identify the minimum number of input parameters that:

- each have a linear slope with respect to the response
- do not interact with each other
- each have enough dynamic range that they can take the response over its full span.

The intent is to maximize the likelihood that systematic process variations such as drifting uniformity can be adequately compensated for over a long period of time.
If such an operating range cannot be established due to nonlinearity or equipment limitations, then it is not practical to control the process by run-by-run techniques absent some major recasting of the process. More than one parameter would be needed generally to give the software the necessary running room to succeed, but certainly the number of input parameters being adjusted need be no larger than the number of responses.

So, had I been free from the constraint of not changing the pre-specified CMP machine recipe(s), this would have given me the opportunity to design for RbR. However, as should be clear by now, this would have required that I construct a complete response surface encompassing all candidate control variables, to permit the inappropriate ones (like back pressure) to be excluded from consideration.

6.2 Manufacturability of RbR Control

There are issues that only arise in a manufacturing setting, as opposed to laboratory or development milieu. These issues determine the practicality of using run-by-run control in manufacturing. First, machines undergo maintenance and repair procedures. Swapping out polish pads or leveling the polish platen are examples of this for CMP machines. Each such procedure alters the machine's state, sometimes imperceptibly, sometimes substantially. This means that using a set process model for run-by-run control is ill-advised. We therefore need a method for adjusting the model after machine maintenance, such that the run-by-run controller continues gives good results over weeks, months, and years of CMP operation. A designed experiment could be run each time, but the more input parameters are involved the more expensive this will be. Polishing several non-product wafers after each maintenance activity adds no product value, and increases cost. The more input parameters are being adjusted run by run, the more expensive this will get, notwithstanding the observation that, with no interactions to model, less than full resolution experiments need be performed.

Second, consider ILD planarization. Each product will have four dielectrics to be polished, and CMP pattern sensitivity means that each dielectric layer will have a different response surface. Multiply this by the number of products made by the fab and the number of individual models to be handled gets quite large. This magnifies the above issue of process recharacterization: we don't want to do this for each model. One possible answer is to use a "blanket" wafer as the control: polishing a single, unpatterned film would be the baseline. This would limit recharacterizing to one type of wafer, but then it would be necessary to accurately translate that response surface to each product response surface at each layer. Perhaps by processing many lots operators would learn how to perform such mappings: whether a 10% change in the slope of a given input parameter for the blanket wafer response means the same change in a patterned wafer, and how it behaves across different ILD layers.

A conceptually cleaner solution would be to use the "rapid response" algorithms described in the early work on run-by-run control[70]. These algorithms were only developed for single-response applications, so this requires further research to extend the approach for multiple-response control. A related, monitor wafer-based approach that does provide multi-variable adaptation, but which is still being developed for nonuniformity control, has been reported by Texas Instruments.[71]

A closely related question to that of long-term model tracking is how much of the variability of the machine needs to be explained by the "linear" model for RbR to work well. If R_a^2 for the regression results of the response surface modeling experiments had been less than, say, 80%, would this have indicated a problem? Or to put it another way, is there a minimally acceptable degree of fit, below which RbR will have difficulty working? How does this interact with the "true" regression results, that is, as the most accurate regression model accrues higher-order terms and interaction terms, how does the R_a^2 threshold change for the RbR model? While there is certainly a place for simulation in exploring these questions, empirical results will also be needed.

A more mundane, but real problem is the need to leverage the computerization of the fab. Requiring operators to enter measurement data and set CMP machine parameters represents an opportunity for errors and wastes operators' time. Clearly, RbR needs to be integrated with the fab CIM system, at a minimum to automatically feed measurement data to the RbR controller, and to permit the controller to download its recipe suggestions to the CMP machine directly.

Finally, who monitors the controller, and how? When a control variable "hits the wall," as back pressure did, what is the appropriate action? From this perspective, methodologies will need to be developed that mesh with the equipment management protocols of the fab. Overall, it is learning via application on the manufacturing line, as opposed to R&D lab learning, that most limits the wider use of RbR as it exists today.

6.3 Technology Insertion Strategy

Consider the back-end CMP proposal as one case on the question of how and whether to insert new technology onto the factory floor. Researchers such as Tyre and Bohn[72] counsel the judicious use of a variety of approaches, including simulation, prototyping, and factory tests, to learn about and apply new manufacturing technology. As I noted in the previous chapter, in the case of semiconductors, with its huge capital investments, there is a school of thought that pushes all but the most narrow process changes out of the factory setting and into the pilot manufacturing stage or earlier, as a matter of manufacturing policy or strategy. This policy implicitly assumes that disruption is unavoidable, and cannot be managed well enough (i.e., that Murphy's Curve cannot be mitigated enough) to escape with a positive NPV for the project.

For the case at hand, this assumption may well be true. For one thing, changing the planarization method for inter-metal dielectrics will affect the entire back end of the CMOS-5 process. So other processing steps will have to be revisited, even if no metal or process shrinks are performed. For example, the etch techniques used to cut vias through dielectric material, to permit electrical connections to be made between metal lines at different levels, are tuned to work with "thin" and "thick" dielectric film topography limits. CMP will alter these limits, so the etch process must be adjusted. The process integration challenge may be quite significant in practice. Because of this, using a prototype fab may be a better strategy for introducing back end CMP than using Fab 4, the volume manufacturing line for CMOS-5.*

As a general policy, however, avoiding all but the most tightly construed innovations on the semiconductor factory floor has its own risks to organizational learning. It assumes that the risk of monetary losses due to disruption is so high that it is worth pushing more learning out of the factory, where experiments have the highest fidelity to production realities. In other industries, there is evidence that using the factory as a learning

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*The irony of this is that Fab 4 previously served as the pilot fab for CMOS-5.

laboratory[73] can be a source of competitive advantage. The question becomes, then, whether to err on the side of less net organizational knowledge and learning but with better factory stability, or more organizational learning amid higher factory disruption.

To help answer this question, more work is needed to create validated models of the disruption caused by introducing new process technology to the factory floor. That is, the "system dynamics" of new technology insertion must be understood, and perhaps the techniques of systems dynamics[74] are applicable to this problem. Also, the analysis framework I used for the back end CMP proposal is only one way in which the question could have been framed (one alternative is the Strategic Cost Management approach[75]). Other lenses may give fresh insight to the questions of risk and payoff.

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Appendix

Data and Regression Results of Experiment #1

Polish Time	Back Pressure	Site 1 Final	Site 1 Init	Site 2 Final	Site 2 Init	Site 3 Final	Site 3 Init	Site 4 Final	Site 4 Init
1.83333	1.5	1299.4	1281.6	1295.3	1299.1	1400.6	1481.3	1423.7	1596.9
1.416667	0.3	1496.1	1398.1	1514.4	1367.9	1571.8	1536.1	1591.5	1677.2
1.83333	1.5	1367.7	1372.4	1415.5	1398.9	1439.5	1624.6	1447.1	1802.2
1.83333	1.5	1384.2	1392.5	1418.2	1388.8	1453.1	1575.8	1466.5	1704.7
1.33333	1.5	1556.6	1472.6	1579.5	1402.2	1637	1614	1668.5	1756.6
1.83333	1.5	1331.1	1439.6	1373.6	1408.1	1412.6	1586.1	1451.8	1694.5
1.83333	3	1327.8	1357.8	1335.4	1335.1	1424.1	1591.8	1431.6	1753.2
1.83333	1.5	1409.4	1480.4	1402.1	1486.7	1473.6	1610.8	1480.5	1768.4
2.25	2.8	1287.1	1466.7	1302.1	1411.1	1344.5	1620.4	1355.9	1746.6
2.25	0.3	1212.5	1441.2	1272.3	1476	1335.2	1660.6	1370.3	1818
2.33333	1.5	1256.2	1370.6	1272.8	1384.3	1317.1	1584.2	1338.9	1726.4
1.83333	0	1298	1312.1	1346.6	1356.6	1397.3	1506	1430	1660.2
1.416667	2.8	1573.9	1553.8	1580.7	1570.4	1621.7	1686.3	1635.2	1855.6
Site 5 Final	**Site 5 Init**	**Site 6 Final**	**Site 6 Init**	**Site 7 Final**	**Site 7 Init**	**Site 8 Final**	**Site 8 Init**	**Site 9 Final**	**Site 9 Init**
1362	1529.2	1299.6	1429.2	1304.1	1322.1	1264.2	1323.8	1282.2	1387.1
1523.5	1575.3	1490.4	1427.2	1564.9	1643.7	1510.3	1583.1	1493.7	1564.8
1447.2	1682.6	1370.9	1447.9	1467.5	1697.4	1427.9	1665.8	1394.4	1625.7
1429.3	1638.5	1382.7	1492.9	1429.5	1630	1386.5	1626.8	1357	1601.1
1635.2	1695.6	1603.1	1555.7	1639.7	1694.7	1611.1	1668	1579.4	1578.6
1397.6	1625.7	1401	1536.6	1427	1645.9	1380.9	1620.4	1395	1586.1
1354.6	1634.2	1315	1501.6	1412.4	1696.7	1339.7	1626.8	1335.8	1589.3
1476.4	1719.9	1385.1	1604.4	1453.9	1684.1	1424.6	1646.9	1407.1	1655.5
1336.8	1723	1252.8	1511.3	1327.4	1703	1293	1682.9	1248.4	1603.2
1325.8	1725.2	1257.9	1533.3	1326.9	1692.5	1288.2	1696.6	1235.8	1653.4
1328.6	1651.2	1234.9	1505	1346	1671.4	1297.3	1654.5	1229.5	1641.7
1379.5	1600.2	1362	1455	1403.7	1623.6	1384.7	1616.1	1351.4	1564.6
1622.8	1763.4	1547.1	1597.9	1605.7	1710.5	1587.8	1716.5	1565	1667.2

Site 1 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.965738595
R Square	0.932651034
Adjusted R Square	0.91918124
Standard Error	32.01001451
Observations	13

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	141892.6774	70946.3387	69.2401892	1.38565E-06
Residual	10	10246.41029	1024.641029		
Total	12	152139.0877			

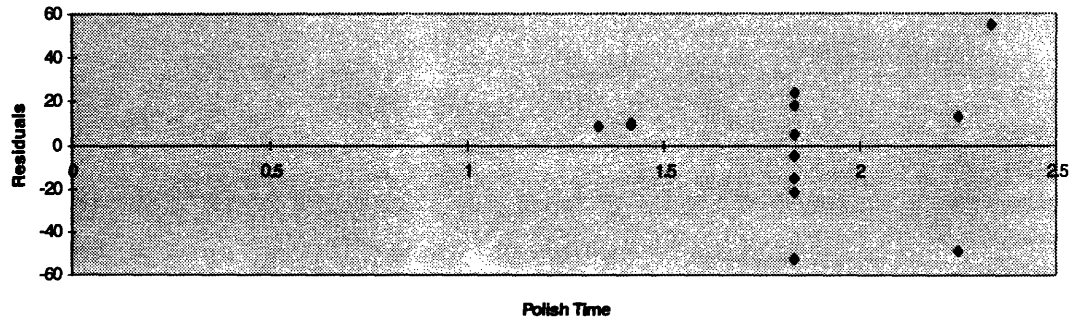
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1200.132843	201.2934166	5.962106774	0.00013897	751.6230828	1648.642602
Polish Time	-295.478222	30.21286383	-9.7798813	1.94854E-06	-362.7966894	-228.1597546
Site 1 Init	0.503860759	0.127737642	3.944497101	0.002754729	0.219243507	0.788478012

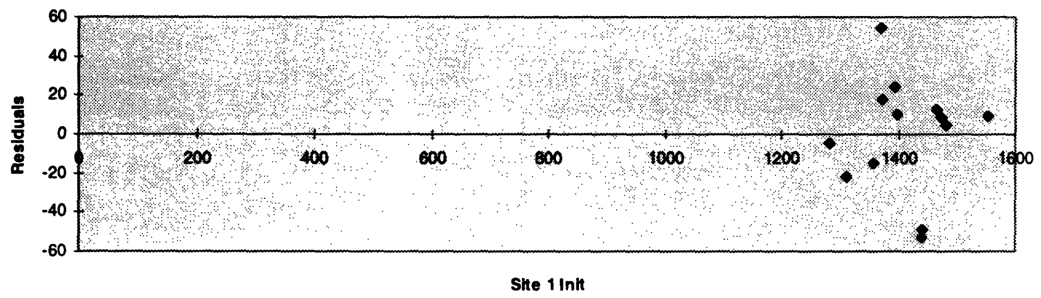
RESIDUAL OUTPUT

Observation	*Predicted Site 1 Final*	*Residuals*	*Standard Residuals*
1	1304.170718	-4.77071768	-0.149038286
2	1485.986422	10.11357806	0.315950437
3	1349.921275	17.7787254	0.555411351
4	1360.048876	24.15112414	0.75448651
5	1548.147234	8.452766348	0.264066308
6	1383.780718	-52.6807176	-1.64575738
7	1342.564908	-14.7649075	-0.461259007
8	1404.338237	5.061763421	0.158130619
9	1274.319418	12.78058165	0.399268224
10	1261.470969	-48.970969	-1.529864005
11	1201.275214	54.92478576	1.71586257
12	1319.538471	-21.5384708	-0.672866638
13	1564.437542	9.462457881	0.295609297

PROBABILITY OUTPUT

Percentile	*Site 1 Final*
3.846153846	1212.5
11.53846154	1256.2
19.23076923	1287.1
26.92307692	1298
34.61538462	1299.4
42.30769231	1327.8
50	1331.1
57.69230769	1367.7
65.38461538	1384.2
73.07692308	1409.4
80.76923077	1496.1
88.46153846	1556.6
96.15384615	1573.9


Polish Time Residual Plot
Residuals
60
40
20
0
-20
-40
-60
0
0.5
1
1.5
2
2.5
Polish Time


Site 1 Init Residual Plot
Residuals
60
40
20
0
-20
-40
-60
200
400
600
800
1000
1200
1400
1600
Site 1 Init

Site 2 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.956925992
R Square	0.915707355
Adjusted R Square	0.898848825
Standard Error	34.18617692
Observations	13

ANOVA

	df	SS	MS	F	Significance F
Regression	2	126960.3438	63480.17192	54.317156	4.25548E-06
Residual	10	11686.94692	1168.694692		
Total	12	138647.2908			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1301.122943	212.8097077	6.114020628	0.0001136	826.9532831	1775.2926
Polish Time	-298.505661	31.48335435	-9.481380465	2.584E-06	-368.6549581	-228.35636
Site 2 Init	0.454372206	0.14088984	3.225017548	0.0090974	0.140450025	0.76829439

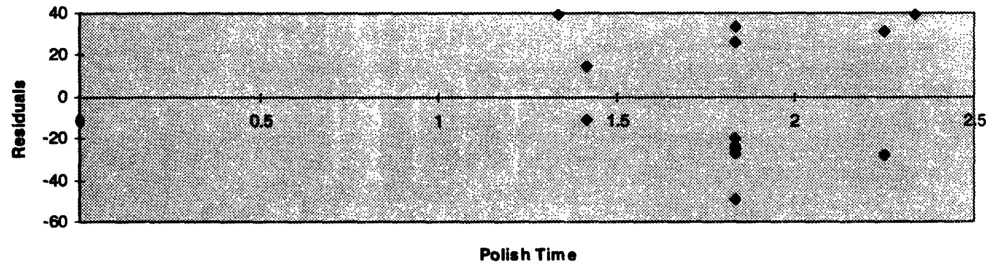
RESIDUAL OUTPUT

Observation	Predicted Site 2 Final	Residuals	Standard Residuals
1	1344.137497	-48.83749735	-1.428574405
2	1499.775664	14.62433615	0.427785072
3	1389.483844	26.0161565	0.76101392
4	1384.894684	33.30531578	0.974233412
5	1540.236102	39.26389774	1.148531403
6	1393.664068	-20.0640678	-0.586905867
7	1360.494897	-25.09489676	-0.734065609
8	1429.377723	-27.27772318	-0.79791675
9	1270.649826	31.45017432	0.919967576
10	1300.138582	-27.83858184	-0.814322757
11	1233.597179	39.20282118	1.146744817
12	1370.263899	-23.66389919	-0.692206656
13	1591.786036	-11.08603555	-0.324284156

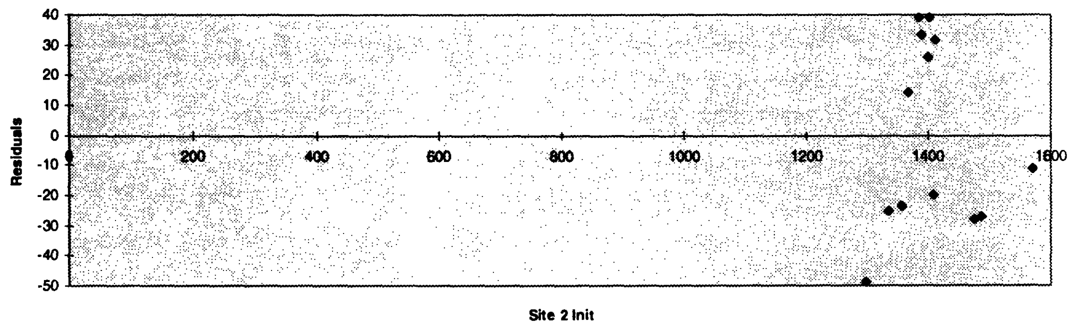
PROBABILITY OUTPUT

Percentile	Site 2 Final
3.846153846	1272.3
11.53846154	1272.8
19.23076923	1295.3
26.92307692	1302.1
34.61538462	1335.4
42.30769231	1346.6
50	1373.6
57.69230769	1402.1
65.38461538	1415.5
73.07692308	1418.2
80.76923077	1514.4
88.46153846	1579.5
96.15384615	1580.7

Polish Time Residual Plot



Site 2 Init Residual Plot



Site 3 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.989885178
R Square	0.979872665
Adjusted R Square	0.973163553
Standard Error	16.99715402
Observations	13

ANOVA

	df	SS	MS	F	Significance F
Regression	3	126583.8477	42194.61591	146.0510281	5.97326E-08
Residual	9	2600.129202	288.9032447		
Total	12	129183.9769			

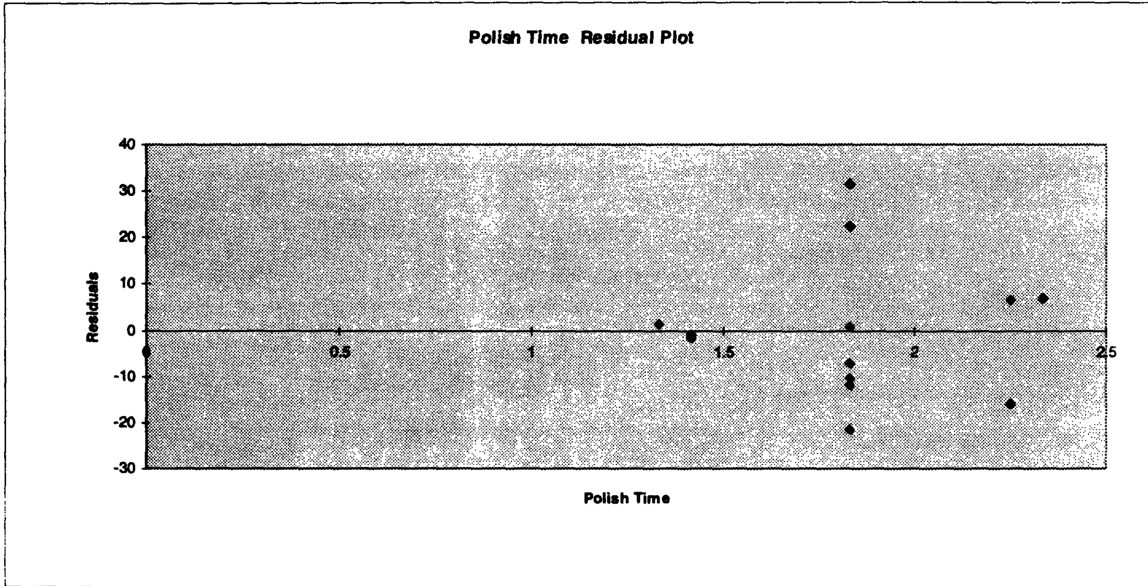
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1958.262465	261.1572589	7.49840335	3.69893E-05	1367.483251	2549.041679
Polish Time	-823.9212678	184.2571472	-4.471583765	0.00155112	-1240.740211	-407.102325
PTsquared	138.5897008	50.15181666	2.763403403	0.02198942	25.13832306	252.0410786
Site 3 Init	0.328191338	0.093187718	3.521830388	0.00649674	0.117385913	0.538996763

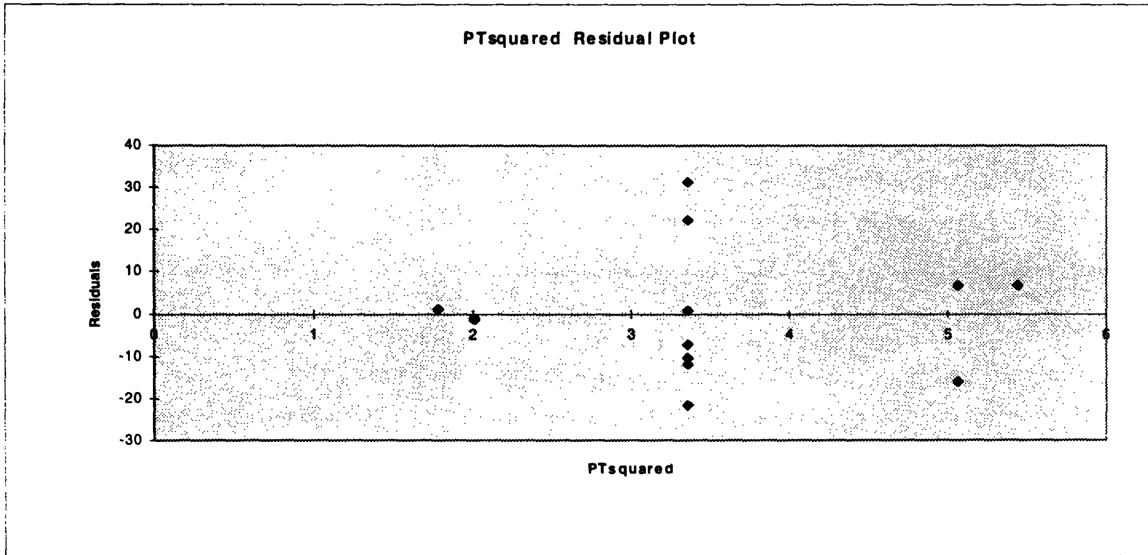
RESIDUAL OUTPUT

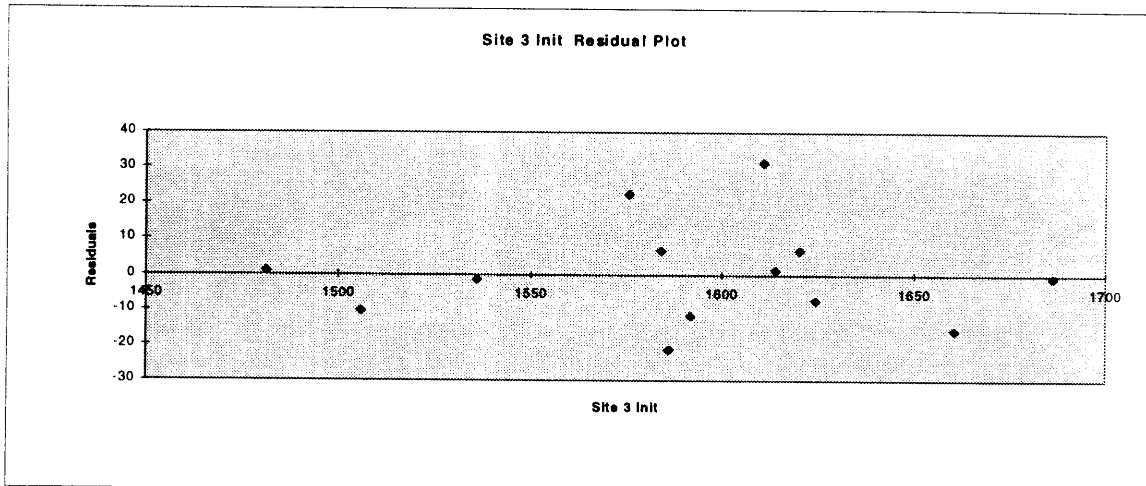
Observation	Predicted Site 3 Final	Residuals	Standard Residuals
1	1399.705353	0.894646819	0.052635095
2	1573.317214	-1.51721356	-0.0892628
3	1446.735172	-7.23517192	-0.42566961
4	1430.719435	22.38056538	1.31672428
5	1635.783285	1.216715335	0.071583474
6	1434.099805	-21.4998054	-1.264906195
7	1435.970496	-11.870496	-0.698381389
8	1442.206131	31.39386855	1.847007359
9	1337.851217	6.648782859	0.39117036
10	1351.044509	-15.8445089	-0.932185995
11	1310.244151	6.855848659	0.403352741
12	1407.811679	-10.5116792	-0.618437605
13	1622.611553	-0.91155253	-0.053629715

PROBABILITY OUTPUT

Percentile	Site 3 Final
3.846153846	1317.1
11.53846154	1335.2
19.23076923	1344.5
26.92307692	1397.3
34.61538462	1400.6
42.30769231	1412.6
50	1424.1
57.69230769	1439.5
65.38461538	1453.1
73.07692308	1473.6
80.76923077	1571.8
88.46153846	1621.7
96.15384615	1637


Polish Time Residual Plot
Residuals
40
30
20
10
0
-10
-20
-30
0.5
1
1.5
2
2.5
Polish Time


PTsquared Residual Plot
Residuals
40
30
20
10
0
-10
-20
-30
0
1
2
3
4
5
6
PTsquared


Site 3 Init Residual Plot
40
30
20
10
0
-10
-20
-30
Residuals
1450
1500
1550
1600
1650
1700
Site 3 Init

Site 4 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.991580282
R Square	0.983231455
Adjusted R Square	0.97764194
Standard Error	15.42921426
Observations	13

ANOVA

	df	SS	MS	F	Significance F
Regression	3	125629.1772	41876.3924	175.906400	2.63032E-08
Residual	9	2142.545874	238.0606526		
Total	12	127771.7231			

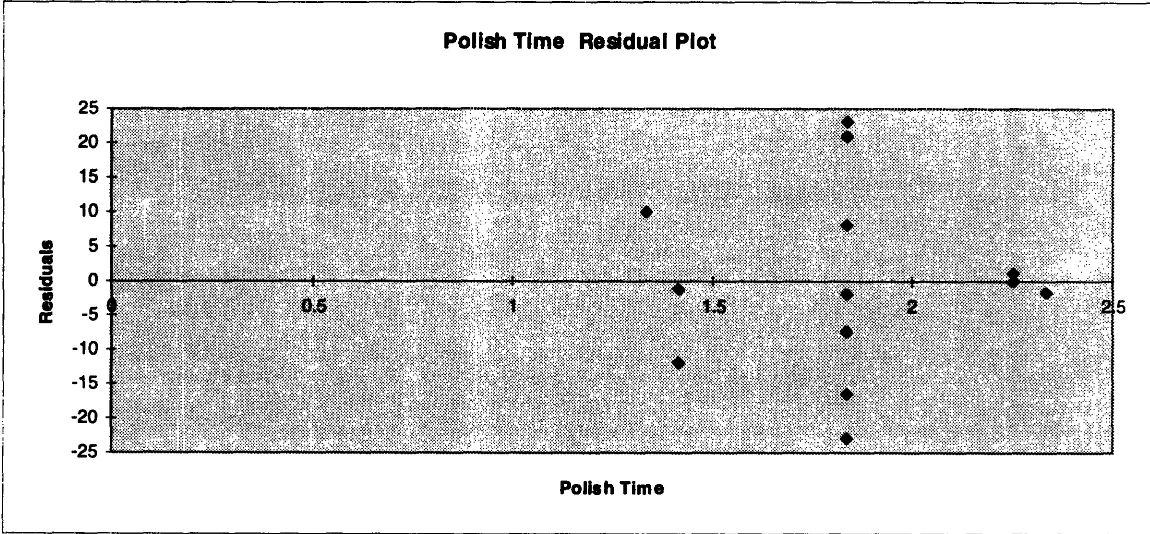
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	2338.979391	217.2278507	10.76740106	1.92741E-06	1847.575478	2830.383304
Polish Time	-1005.122703	163.6919637	-6.140330167	0.00017070	-1375.419933	-634.825472
PTsquared	188.957196	44.46727873	4.249353714	0.00214451	88.36514626	289.5492458
Site 4 Init	0.184309469	0.067678668	2.723302247	0.02348054	0.031209568	0.337409369

RESIDUAL OUTPUT

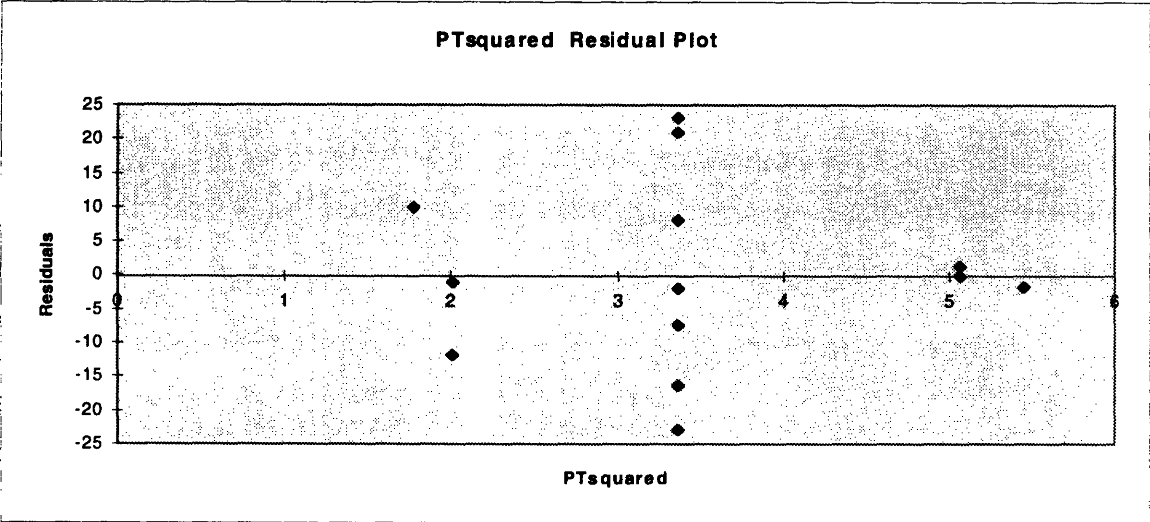
Observation	Predicted Site 4 Final	Residuals	Standard Residuals
1	1425.684357	-1.98435662	-0.128610348
2	1603.405997	-11.9059969	-0.771652834
3	1463.523091	-16.4230905	-1.064415221
4	1445.552917	20.94708267	1.357624719
5	1658.497703	10.00229679	0.648270004
6	1443.672961	8.127039253	0.526730598
7	1454.491927	-22.8919266	-1.483674163
8	1457.29343	23.20656953	1.50406684
9	1355.964032	-0.0640316	-0.004150023
10	1369.123728	1.17627235	0.076236698
11	1340.651906	-1.75190634	-0.113544754
12	1437.351146	-7.35114598	-0.476443314
13	1636.286806	-1.0868061	-0.070438201

PROBABILITY OUTPUT

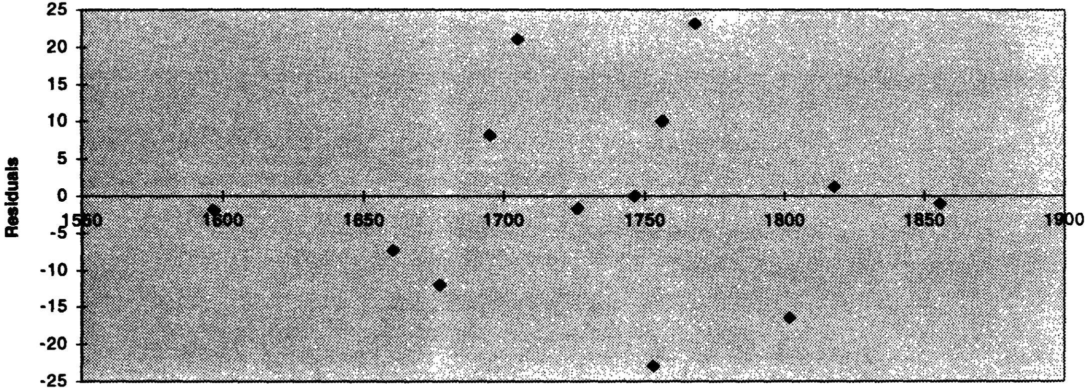
Percentile	Site 4 Final
3.846153846	1338.9
11.53846154	1355.9
19.23076923	1370.3
26.92307692	1423.7
34.61538462	1430
42.30769231	1431.6
50	1447.1
57.69230769	1451.8
65.38461538	1466.5
73.07692308	1480.5
80.76923077	1591.5
88.46153846	1635.2
96.15384615	1668.5



Polish Time Residual Plot
Residuals
25
20
15
10
5
0
-5
-10
-15
-20
-25
0
0.5
1
1.5
2
2.5
Polish Time



PTsquared Residual Plot
Residuals
25
20
15
10
5
0
-5
-10
-15
-20
-25
0
1
2
3
4
5
6
PTsquared


Site 4 Init Residual Plot
Residuals
25
20
15
10
5
0
-5
-10
-15
-20
-25
1600
1650
1700
1750
1800
1850
1900
Site 4 Init

Site 5 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.99276416
R Square	0.98558067
Adjusted R Square	0.97528115
Standard Error	16.6227054
Observations	13

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	132205.192	26441.038	95.69188	2.74702E-06
Residual	7	1934.200354	276.31434		
Total	12	134139.3923			

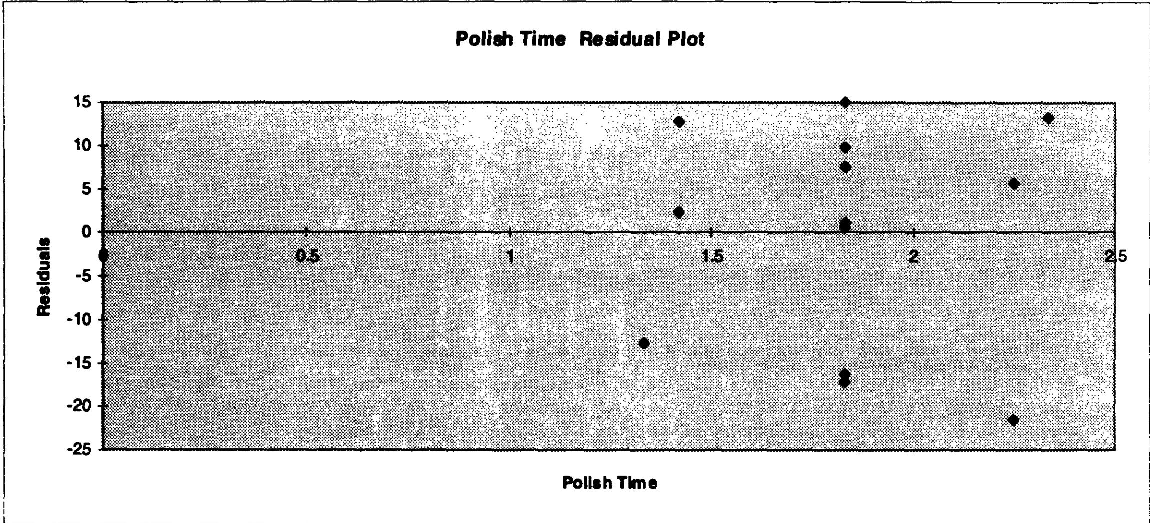
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1591.0748	252.7766816	6.2943892	0.0004064	993.3533595	2188.7962
Polish Time	-902.44292	182.4295028	-4.946804	0.0016623	-1333.81984	-471.066
Back Pressure	52.2373347	16.31095281	3.2025925	0.0150117	13.66808775	90.806582
PTsquared	162.148619	49.76850605	3.2580568	0.0139017	44.46488726	279.83235
BPsquared	-18.781231	5.02765046	-3.735588	0.0073049	-30.6697272	-6.8927358
Site 5 Init	0.55177654	0.085318933	6.4672227	0.0003446	0.35002947	0.7535236

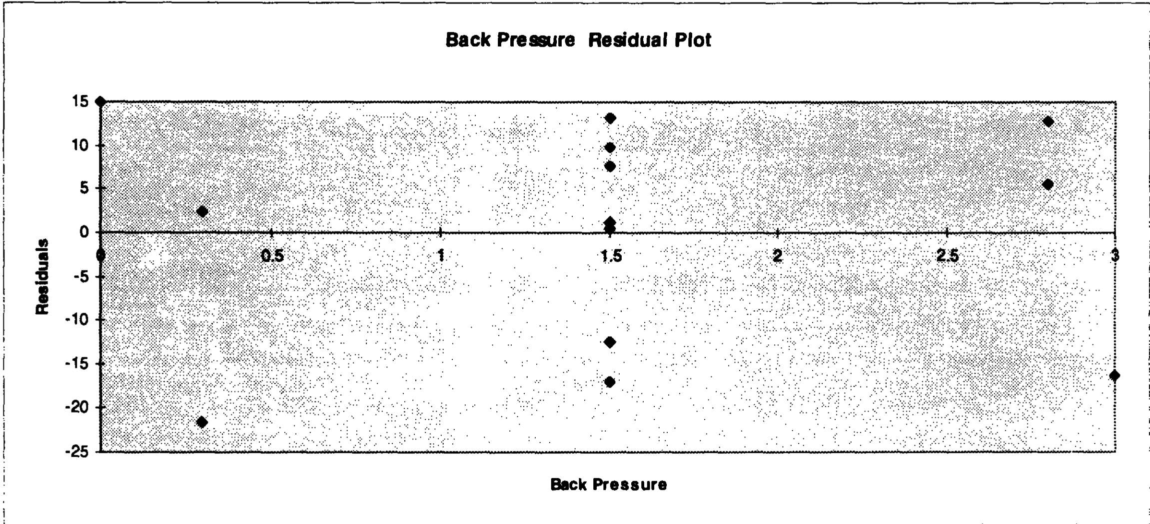
RESIDUAL OUTPUT

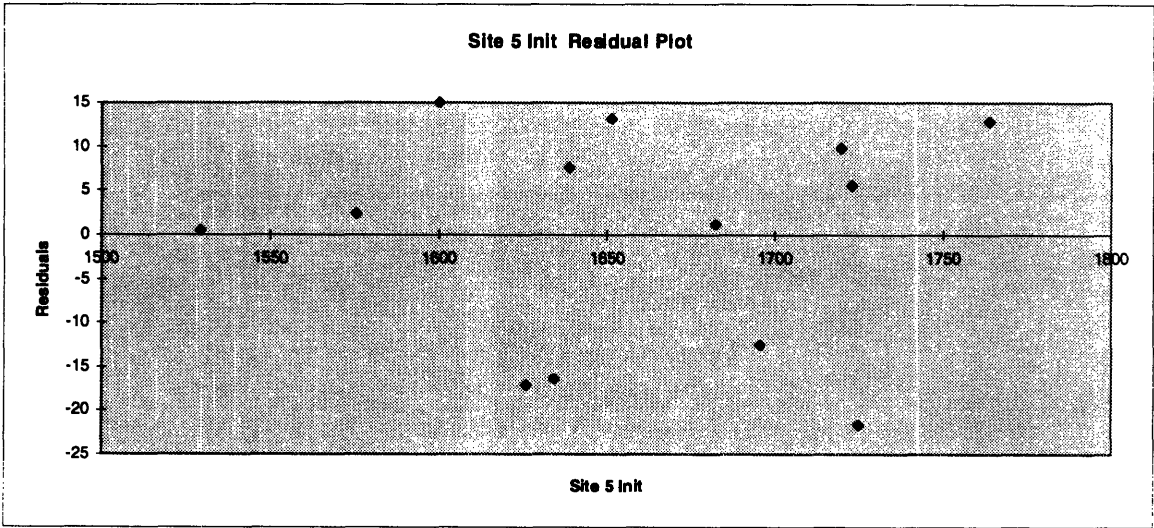
Observation	*Predicted Site 5 Final*	*Residuals*	*Standard Residuals*
1	1361.47057	0.529431229	0.0318499
2	1521.23175	2.268247058	0.1364547
3	1446.11309	1.086909359	0.065387
4	1421.77975	7.520254955	0.4524086
5	1647.77233	-12.5723308	-0.756335
6	1414.71701	-17.11700528	-1.029736
7	1370.9898	-16.38979554	-0.985988
8	1466.69436	9.705644263	0.5838787
9	1331.18629	5.613708981	0.3377133
10	1347.36141	-21.56140653	-1.297106
11	1315.37547	13.22452821	0.7955701
12	1364.54847	14.95152787	0.8994642
13	1610.05971	12.74028622	0.7664388

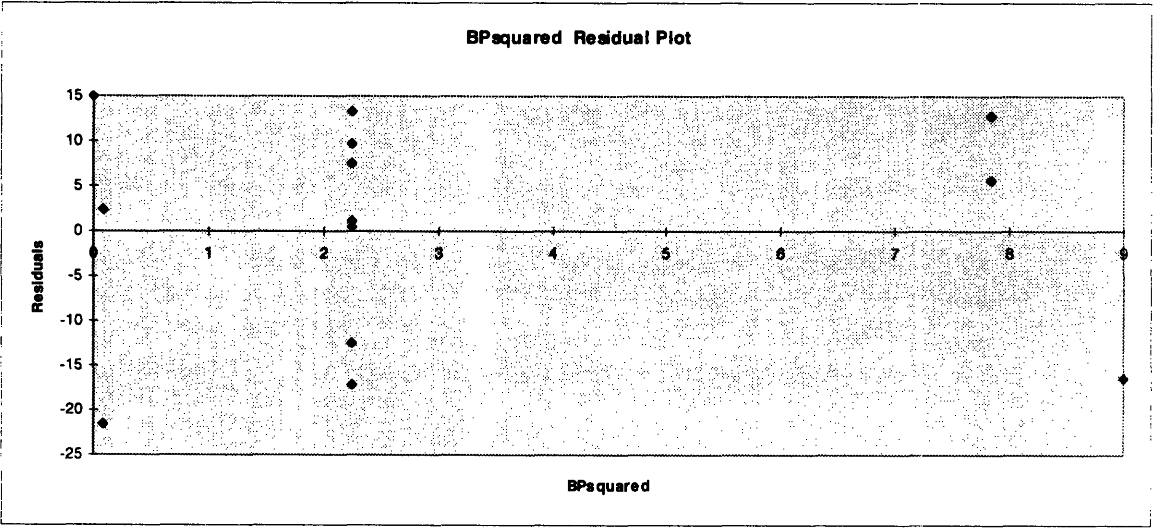
PROBABILITY OUTPUT

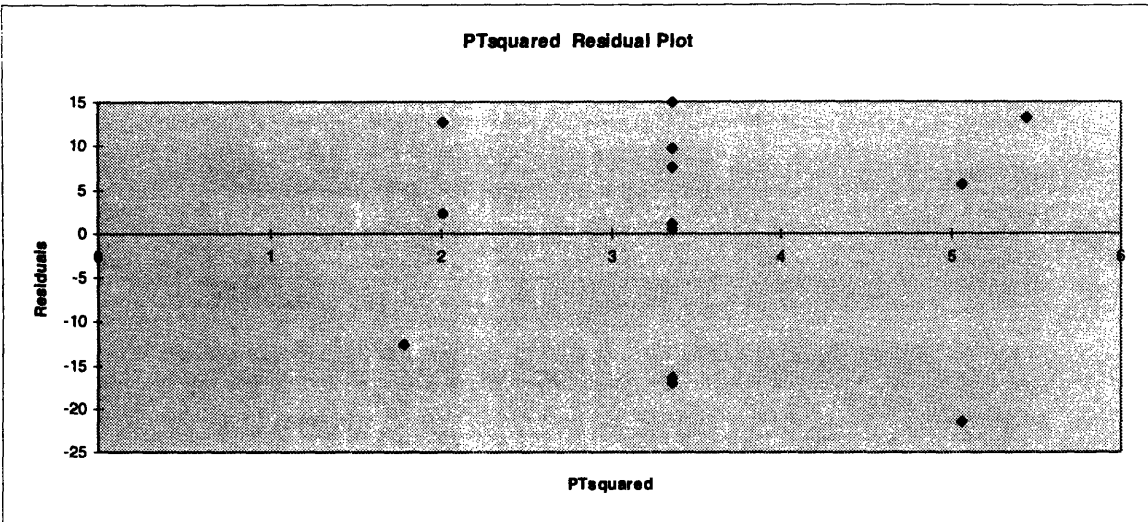
Percentile	*Site 5 Final*
3.846153846	1325.8
11.53846154	1328.6
19.23076923	1336.8
26.92307692	1354.6
34.61538462	1362
42.30769231	1379.5
50	1397.6
57.69230769	1429.3
65.38461538	1447.2
73.07692308	1476.4
80.76923077	1523.5
88.46153846	1622.8
96.15384615	1635.2


Polish Time Residual Plot
Residuals
Polish Time
15
10
5
0
-5
-10
-15
-20
-25
0
0.5
1
1.5
2
2.5


Back Pressure Residual Plot
Residuals
Back Pressure
15
10
5
0
-5
-10
-15
-20
-25
0
0.5
1
1.5
2
2.5
3


Site 5 Init Residual Plot
15
10
5
0
-5
-10
-15
-20
-25
1500
1550
1600
1650
1700
1750
1800
Residuals
Site 5 Init


BPsquared Residual Plot
15
10
5
0
-5
-10
-15
-20
-25
1
2
3
4
5
6
7
8
9
Residuals
BPsquared


PTsquared Residual Plot
Residuals
15
10
5
0
-5
-10
-15
-20
-25
0
1
2
3
4
5
6
PTsquared

Site 6 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.967458124
R Square	0.935975221
Adjusted R Square	0.923170265
Standard Error	31.34815727
Observations	13

ANOVA

	df	SS	MS	F	Significance F
Regression	2	143661.4673	71830.73364	73.094764	1.07582E-06
Residual	10	9827.069639	982.7069639		
Total	12	153488.5369			

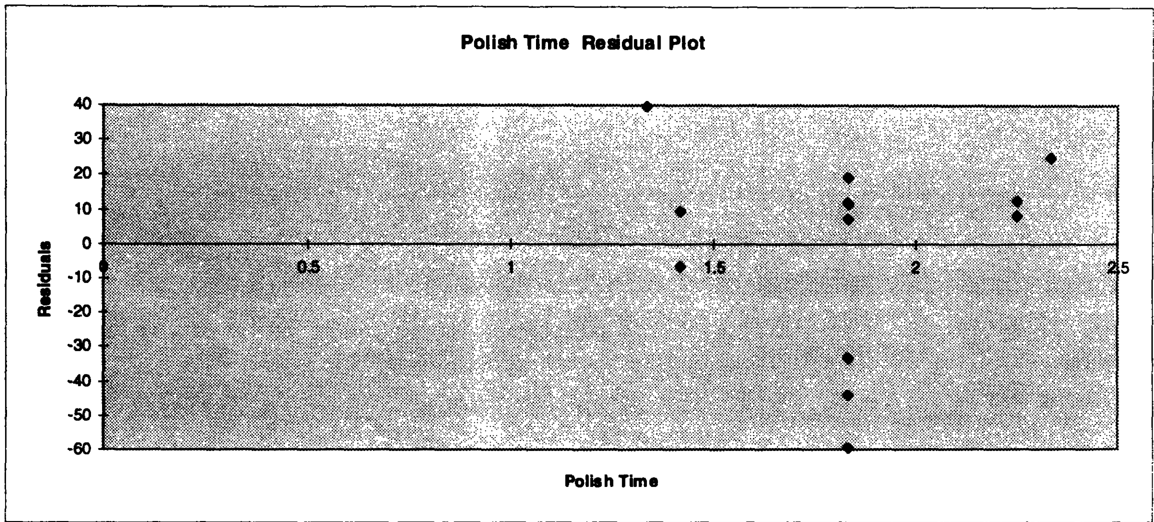
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1344.392015	245.3836087	5.478736018	0.0002697	797.6431683	1891.14086
Polish Time	-331.7663133	28.77154689	-11.53105582	4.246E-07	-395.873326	-267.6593
Site 6 Init	0.425170984	0.156146433	2.72289911	0.0214533	0.077254989	0.77308698

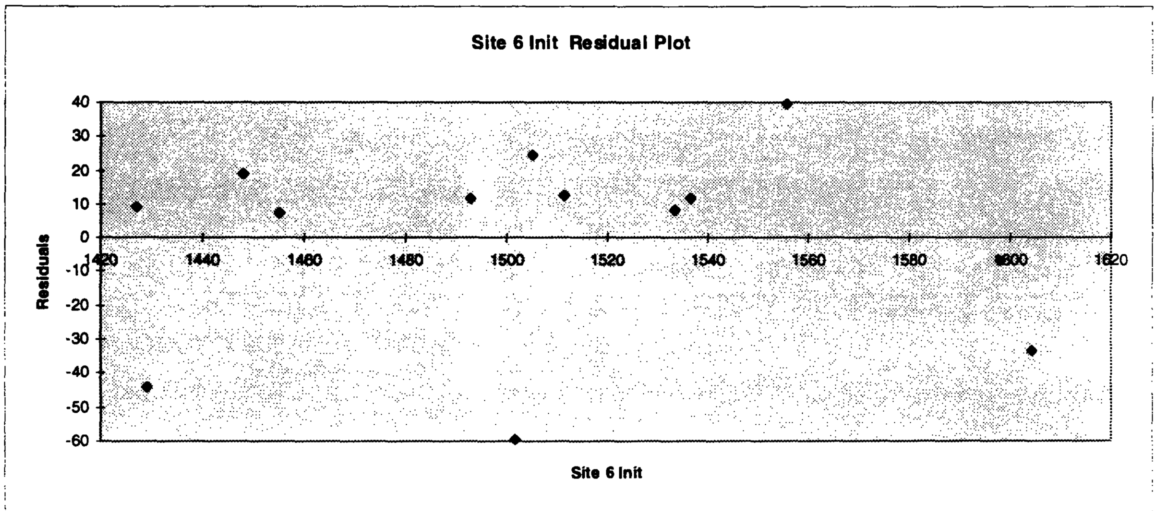
RESIDUAL OUTPUT

Observation	Predicted Site 6 Final	Residuals	Standard Residuals
1	1343.808144	-44.20814387	-1.410231022
2	1481.193766	9.206234216	0.293677046
3	1351.758841	19.14115874	0.610599168
4	1370.891536	11.80846448	0.376687675
5	1563.47543	39.62457004	1.264015926
6	1389.471508	11.52849249	0.367756624
7	1374.590523	-59.59052308	-1.900925869
8	1418.2981	-33.1981002	-1.059012813
9	1240.478718	12.32128226	0.393046461
10	1249.832479	8.067520623	0.257352308
11	1210.152948	24.74705224	0.789426059
12	1354.777555	7.222444756	0.230394555
13	1553.770453	-6.670452693	-0.212786118

PROBABILITY OUTPUT

Percentile	Site 6 Final
3.846153846	1234.9
11.53846154	1252.8
19.23076923	1257.9
26.92307692	1299.6
34.61538462	1315
42.30769231	1362
50	1370.9
57.69230769	1382.7
65.38461538	1385.1
73.07692308	1401
80.76923077	1490.4
88.46153846	1547.1
96.15384615	1603.1


Polish Time Residual Plot
40
30
20
10
0
-10
-20
-30
-40
-50
-60
0
0.5
1
1.5
2
2.5
Residuals
Polish Time


Site 6 Init Residual Plot
40
30
20
10
0
-10
-20
-30
-40
-50
-60
1420
1440
1460
1480
1500
1520
1540
1560
1580
1600
1620
Residuals
Site 6 Init

Site 7 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.99663319
R Square	0.993277716
Adjusted R Square	0.988476084
Standard Error	11.55400634
Observations	13

ANOVA

	df	SS	MS	F	Significance F
Regression	5	138075.6423	27615.12845	206.86255	1.91776E-07
Residual	7	934.4654382	133.4950626		
Total	12	139010.1077			

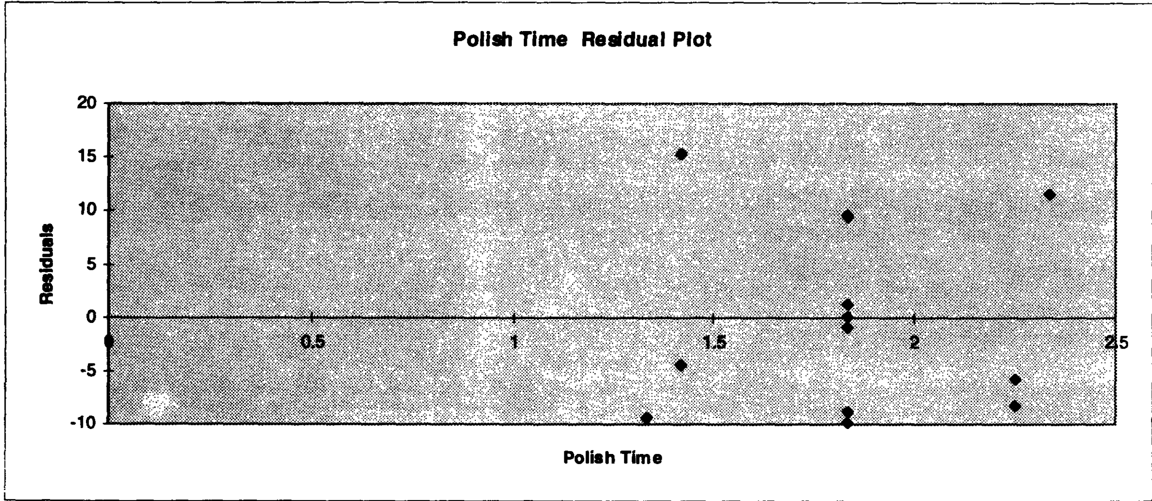
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1820.058002	143.7326897	12.6627979	4.429E-06	1480.184441	2159.931562
Polish Time	-886.46709	123.3520723	-7.186479103	0.0001796	-1178.14818	-594.785997
Back Pressure	45.89207394	11.4727104	4.000107413	0.0051892	18.76344409	73.02070378
PTsquared	158.5933618	33.53384307	4.729352417	0.0021342	79.29847993	237.8882436
BPsquared	-15.6182019	3.606955899	-4.330022964	0.0034378	-24.1472912	-7.08911258
Site 7 Init	0.41028564	0.036759582	11.1613249	1.032E-05	0.323363102	0.497208177

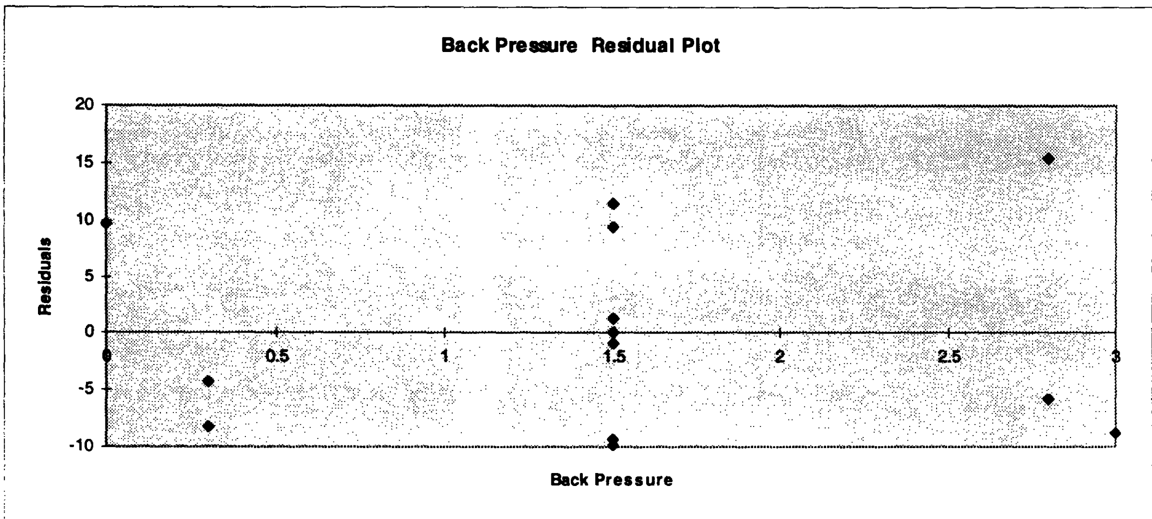
RESIDUAL OUTPUT

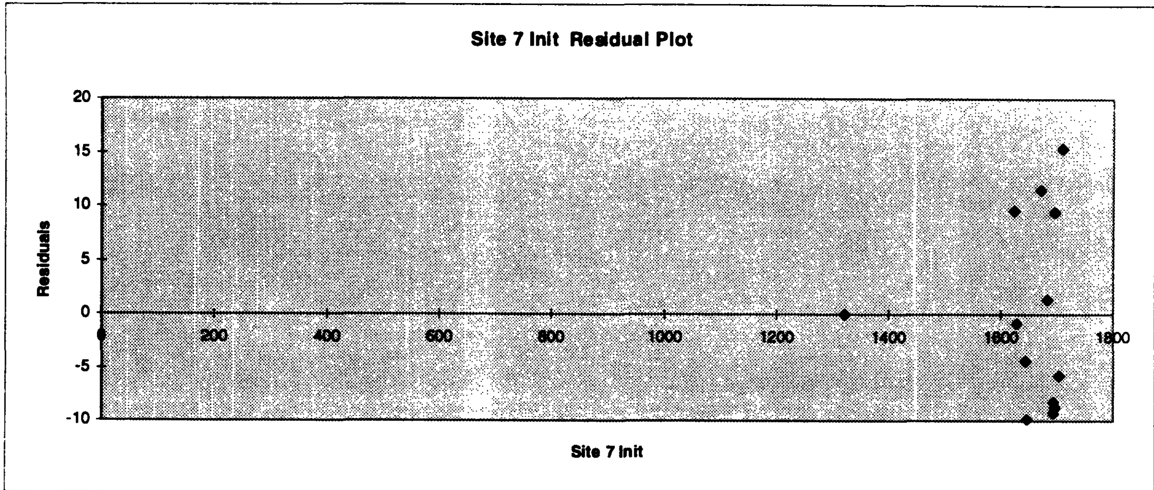
Observation	Predicted Site 7 Final	Residuals	Standard Residuals
1	1304.054048	0.045951715	0.003977124
2	1569.266181	-4.366180737	-0.377893227
3	1458.034249	9.465751089	0.819261372
4	1430.380997	-0.880996787	-0.076250329
5	1649.053866	-9.353866461	-0.80957775
6	1436.904538	-9.90453846	-0.857238447
7	1421.162297	-8.76229723	-0.758377395
8	1452.57745	1.322550099	0.114466797
9	1333.153492	-5.75349229	-0.497965132
10	1335.156373	-8.25637274	-0.714589597
11	1334.536114	11.46388561	0.992200045
12	1394.058012	9.641988	0.834514688
13	1590.362382	15.33761819	1.327471851

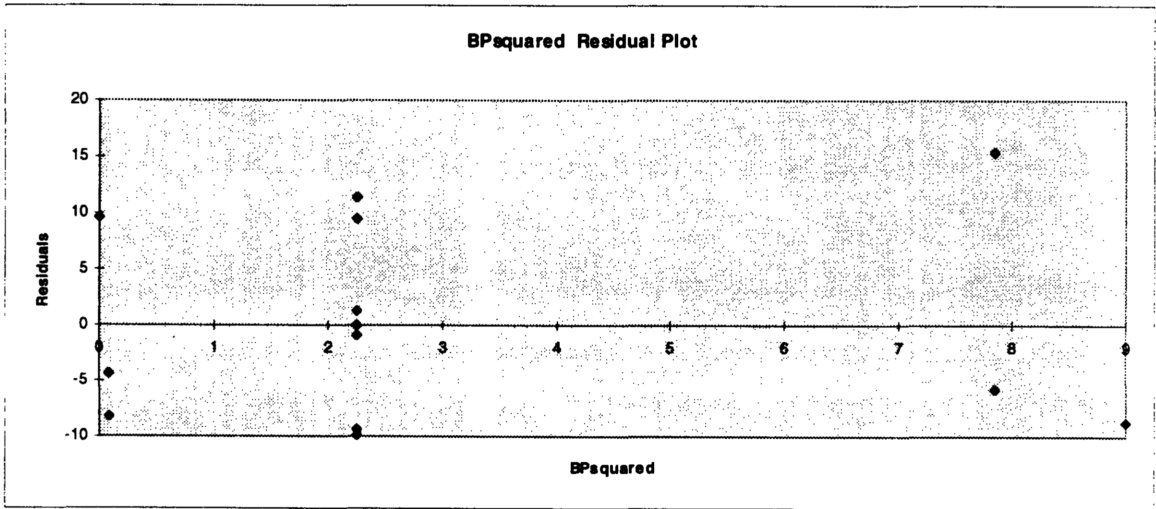
PROBABILITY OUTPUT

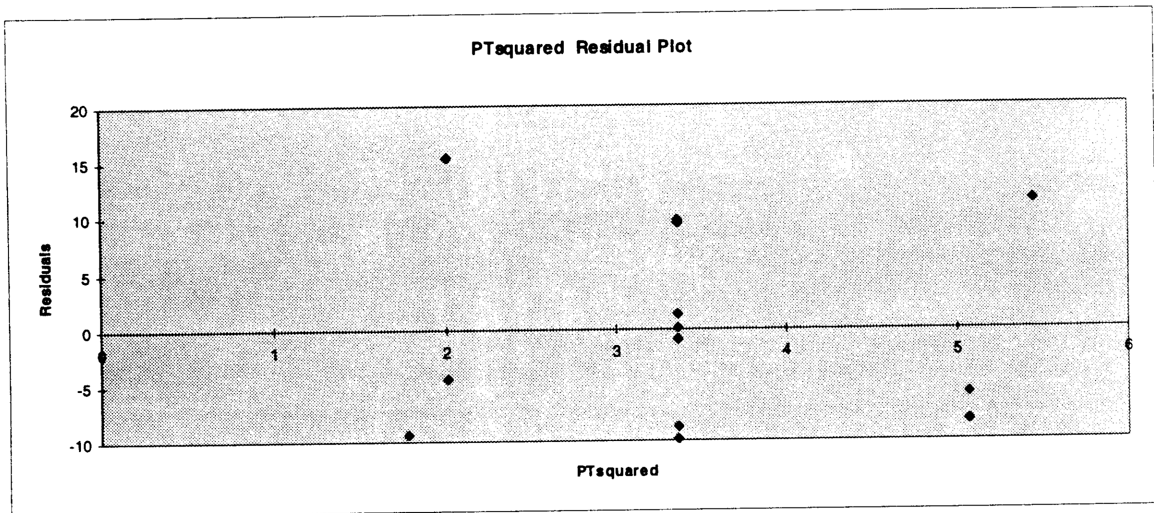
Percentile	Site 7 Final
3.846153846	1304.1
11.53846154	1326.9
19.23076923	1327.4
26.92307692	1346
34.61538462	1403.7
42.30769231	1412.4
50	1427
57.69230769	1429.5
65.38461538	1453.9
73.07692308	1467.5
80.76923077	1564.9
88.46153846	1605.7
96.15384615	1639.7


Polish Time Residual Plot
20
15
10
5
0
-5
-10
0.5
1
1.5
2
2.5
Residuals
Polish Time


Back Pressure Residual Plot
20
15
10
5
0
-5
-10
0.5
1
1.5
2
2.5
3
Residuals
Back Pressure


Site 7 Init Residual Plot
20
15
10
5
0
-5
-10
Residuals
200
400
600
800
1000
1200
1400
1600
1800
Site 7 Init


BPsquared Residual Plot
20
15
10
5
0
-5
-10
Residuals
0
1
2
3
4
5
6
7
8
9
BPsquared


PTsquared Residual Plot
20
15
10
5
0
-5
-10
Residuals
1
2
3
4
5
6
PTsquared

Site 8 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.991871493
R Square	0.983809058
Adjusted R Square	0.972244099
Standard Error	18.67214051
Observations	13

ANOVA

	df	SS	MS	F	Significance F
Regression	5	148294.4674	29658.89348	85.0680996	4.11243E-06
Residual	7	2440.541817	348.648831		
Total	12	150735.0092			

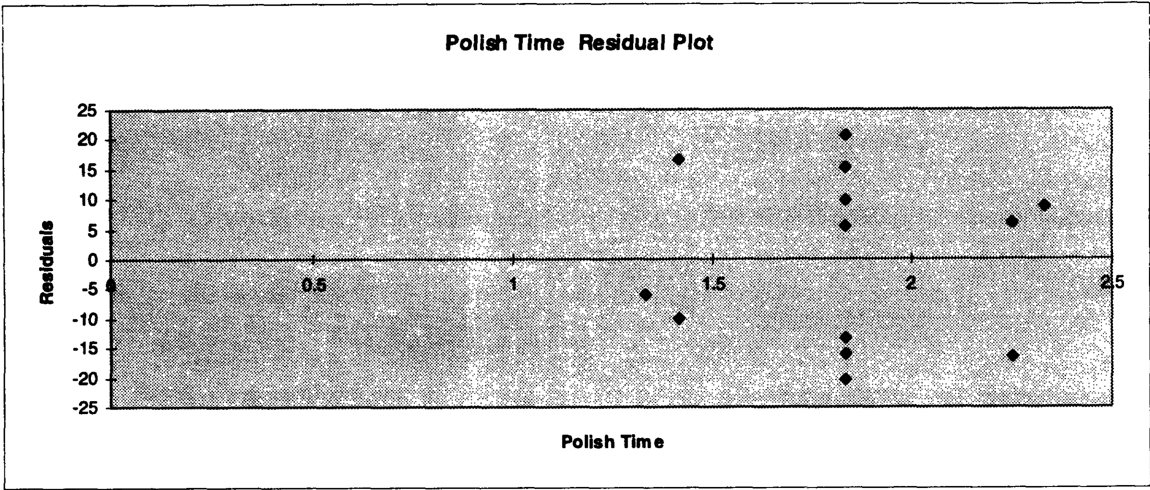
	Coefficients	Std Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1695.952401	239.9685237	7.067395233	0.0001993	1128.517416	2263.387386
Polish Time	-861.8479879	202.5990089	-4.253959547	0.00377463	-1340.91817	- 382.7778009
Back Pressure	44.02603285	18.48894896	2.381207983	0.04879537	0.306647041	87.74541866
PTsquared	147.2226267	55.20462271	2.666853236	0.03214602	16.68453045	277.760723
BPsquared	-15.67594387	5.792550499	-2.706224809	0.03036435	-29.3731395	- 1.978748279
Site 8 Init	0.466208966	0.062717313	7.433497139	0.00014523	0.317906193	0.614511739

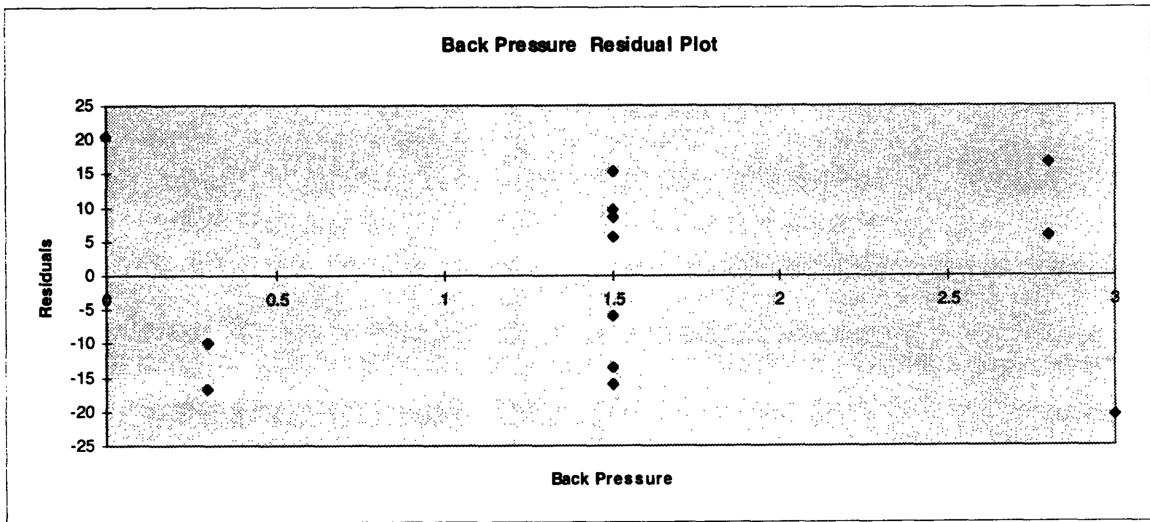
RESIDUAL OUTPUT

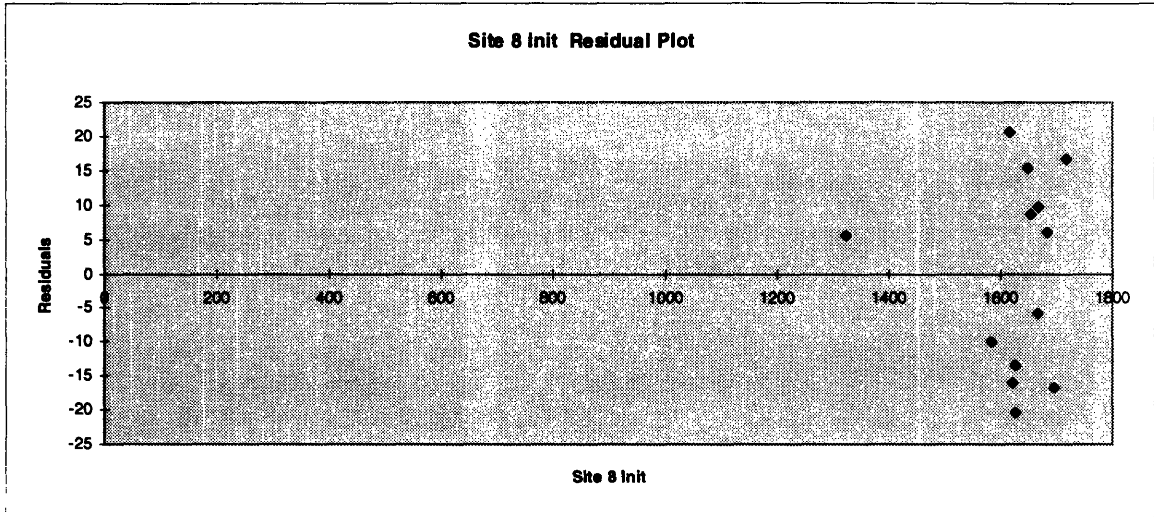
Observation	Predicted Site 8 Final	Residuals	Std. Residuals
1	1258.664967	5.535032892	0.296432693
2	1520.321106	-10.02110586	-0.536687578
3	1418.108433	9.791566622	0.524394438
4	1399.926284	-13.42628372	-0.719054343
5	1616.955595	-5.855594745	-0.313600615
6	1396.942546	-16.04254634	-0.859170181
7	1360.152712	-20.45271188	-1.095359789
8	1409.297084	15.30291607	0.819558747
9	1287.065536	5.934463825	0.317824506
10	1304.876082	-16.67608186	-0.893099635
11	1288.630084	8.669916216	0.464323638
12	1364.169672	20.53032779	1.099516565
13	1571.089899	16.71010097	0.894921553

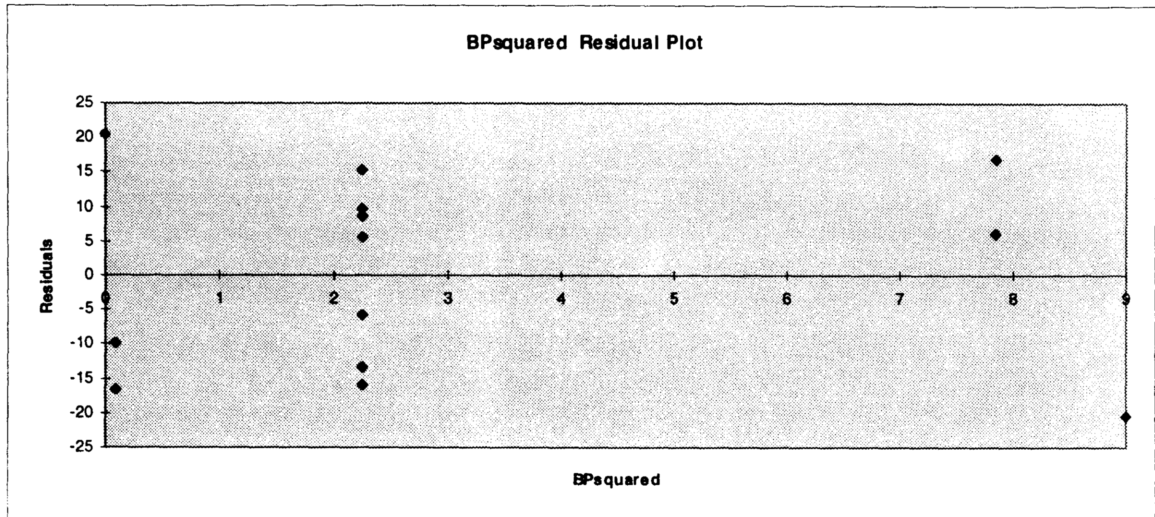
PROBABILITY OUTPUT

Percentile	Site 8 Final
3.846153846	1264.2
11.53846154	1288.2
19.23076923	1293
26.92307692	1297.3
34.61538462	1339.7
42.30769231	1380.9
50	1384.7
57.69230769	1386.5
65.38461538	1424.6
73.07692308	1427.9
80.76923077	1510.3
88.46153846	1587.8
96.15384615	1611.1


Polish Time Residual Plot
25
20
15
10
5
0
-5
-10
-15
-20
-25
Residuals
0
0.5
1
1.5
2
2.5
Polish Time


Back Pressure Residual Plot
25
20
15
10
5
0
-5
-10
-15
-20
-25
Residuals
0
0.5
1
1.5
2
2.5
3
Back Pressure


Site 8 Init Residual Plot
Residuals
25
20
15
10
5
0
-5
-10
-15
-20
-25
0
200
400
600
800
1000
1200
1400
1600
1800
Site 8 Init


BPsquared Residual Plot
Residuals
BPsquared
25
20
15
10
5
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-5
-10
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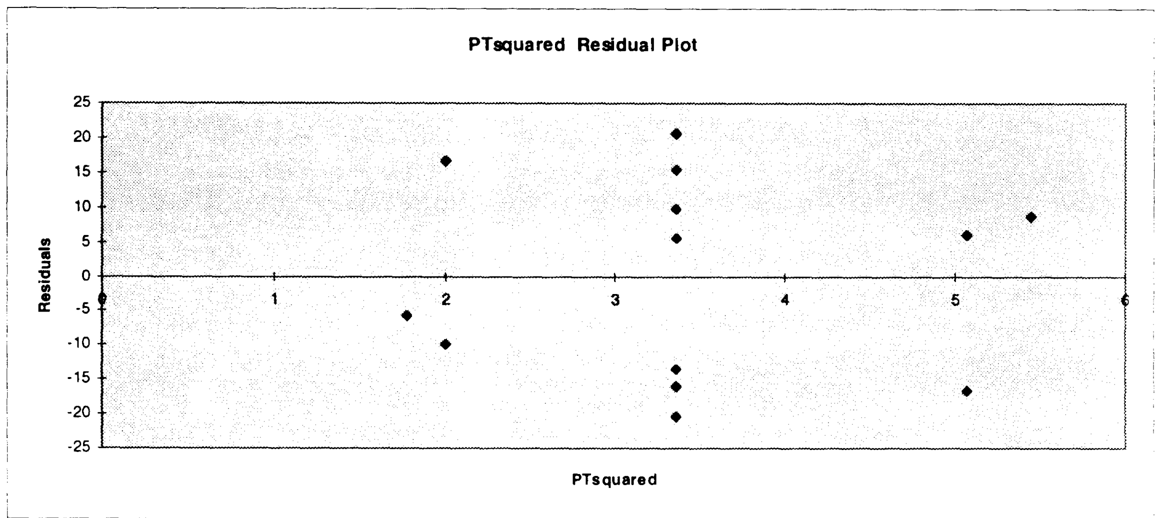
4
5
6
7
8
9


PTsquared Residual Plot
Residuals
PTsquared
25
20
15
10
5
0
-5
-10
-15
-20
-25
0
1
2
3
4
5
6

Site 9 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.985449512
R Square	0.971110741
Adjusted R Square	0.965332889
Standard Error	21.59198951
Observations	13

ANOVA

	df	SS	MS	F	Significance F
Regression	2	156717.563	78358.78148	168.074703	2.01225E-08
Residual	10	4662.140109	466.2140109		
Total	12	161379.7031			

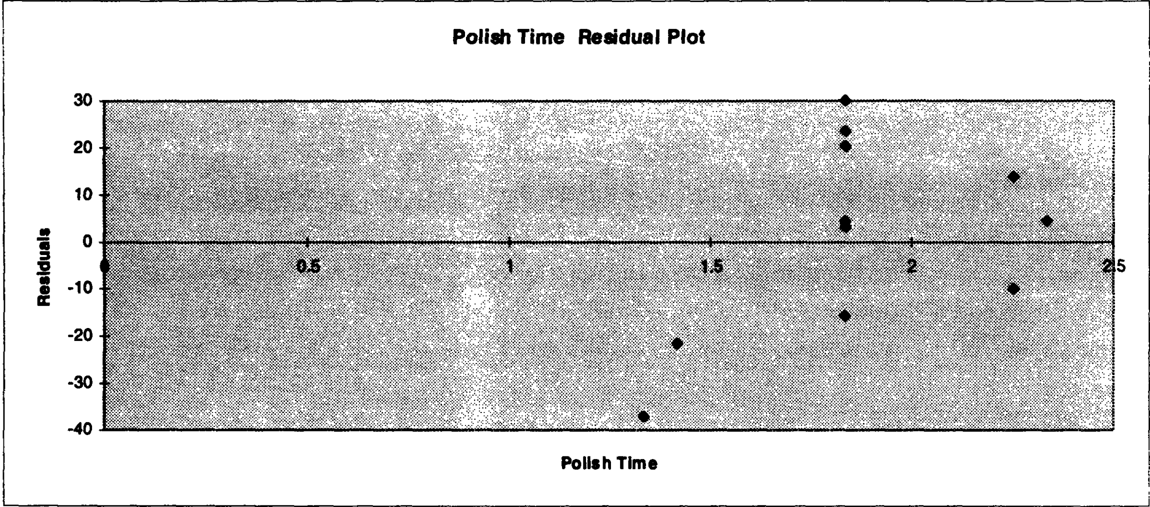
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1295.819828	140.3198979	9.23475464	3.2809E-06	983.1675577	1608.4721
Polish Time	-363.2377511	19.99800207	-18.16370205	5.4905E-09	-407.7960842	-318.679418
Site 9 Init	0.46751947	0.088543463	5.280112781	0.00035759	0.270232306	0.66480663

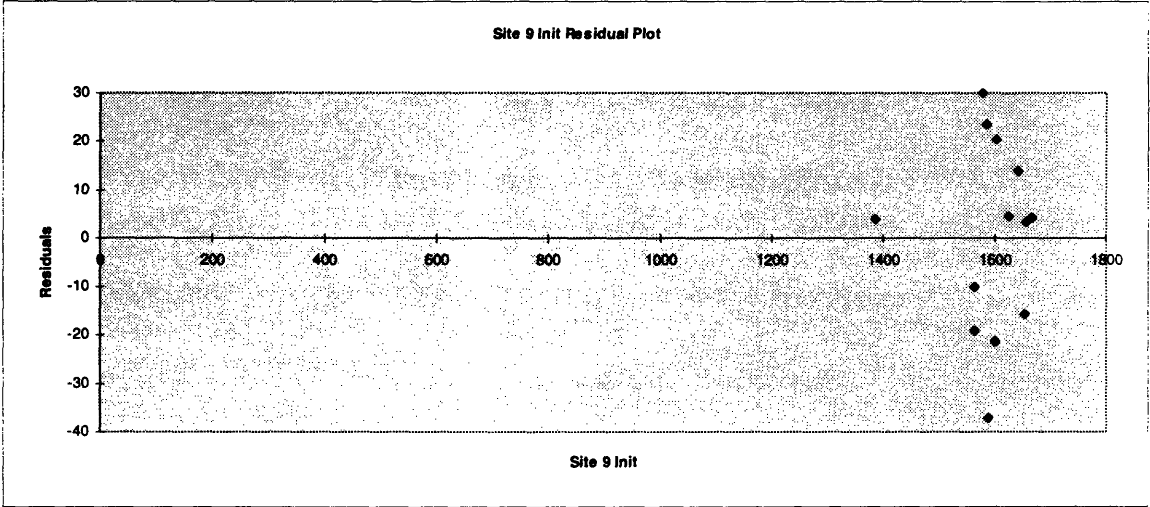
RESIDUAL OUTPUT

Observation	Predicted Site 9 Final	Residuals	Standard Residuals
1	1278.380208	3.819792059	0.176907832
2	1512.807481	-19.10748	-0.884933774
3	1389.930354	4.469646486	0.207004847
4	1378.429375	-21.42937	-0.992468737
5	1549.529062	29.87093796	1.383426847
6	1371.416582	23.5834175	1.092229945
7	1372.912645	-37.1126448	-1.718815433
8	1403.862434	3.237566276	0.149942935
9	1228.062102	20.33789754	0.941918647
10	1251.53158	-15.7316	-0.728584082
11	1215.791789	13.70821053	0.634874824
12	1361.364914	-9.96491	-0.46150976
13	1560.681474	4.318525505	0.20000591

PROBABILITY OUTPUT

Percentile	Site 9 Final
3.846153846	1229.5
11.53846154	1235.8
19.23076923	1248.4
26.92307692	1282.2
34.61538462	1335.8
42.30769231	1351.4
50	1357
57.69230769	1394.4
65.38461538	1395
73.07692308	1407.1
80.76923077	1493.7
88.46153846	1565
96.15384615	1579.4


Polish Time Residual Plot
30
20
10
0
-10
-20
-30
-40
Residuals
0.5
1
1.5
2
2.5
Polish Time


Site 9 Init Residual Plot
30
20
10
0
-10
-20
-30
-40
Residuals
200
400
600
800
1000
1200
1400
1600
1800
Site 9 Init

Site 3 First Order Model Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.981221101
R Square	0.962794848
Adjusted R Square	0.955353818
Standard Error	21.9232969
Observations	13

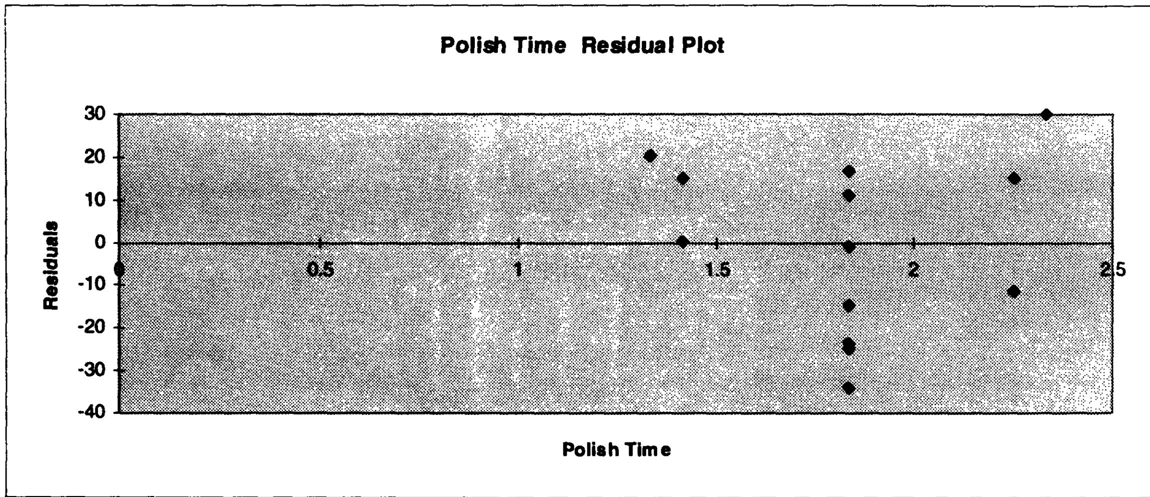
ANOVA

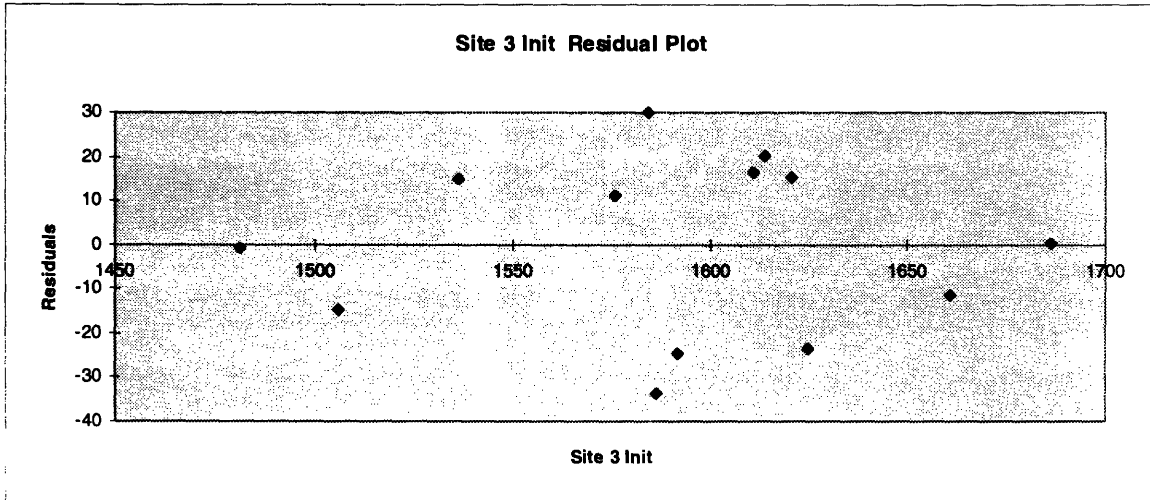
	df	SS	MS	F	Significance F
Regression	2	124377.6675	62188.83373	129.3899907	7.12878E-08
Residual	10	4806.309468	480.6309468		
Total	12	129183.9769			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1345.767823	178.1476336	7.554227891	1.93856E-05	948.8300901	1742.705555
Polish Time	-316.5649366	20.07895168	-15.76600918	2.16448E-08	-361.3036367	-271.8262365
Site 3 Init	0.429341134	0.110535127	3.884205359	0.003038065	0.183053479	0.675628788

RESIDUAL
OUTPUT

Observation	Predicted Site 3 Final	Residuals	Standard Residuals
1	1401.381793	-0.781793466	-0.035660397
2	1556.811744	14.98825551	0.683667953
3	1462.906378	-23.40637791	-1.067648631
4	1441.954531	11.14546941	0.508384732
5	1616.63783	20.36216982	0.928791409
6	1446.376744	-33.77674427	-1.540678139
7	1448.823989	-24.72398873	-1.127749574
8	1456.98147	16.61852973	0.758030592
9	1329.201088	15.29891175	0.697838096
10	1346.460602	-11.26060182	-0.513636333
11	1287.278528	29.82147217	1.360264029
12	1411.986519	-14.68651947	-0.669904693
13	1621.298783	0.401217245	0.018300954


Polish Time Residual Plot
30
20
10
0
-10
-20
-30
-40
Residuals
0
0.5
1
1.5
2
2.5
Polish Time


Site 3 Init Residual Plot
30
20
10
0
-10
-20
-30
-40
Residuals
1450
1500
1550
1600
1650
1700
Site 3 Init

Site 4 First Order Model Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.974468138
R Square	0.949588152
Adjusted R Square	0.939505782
Standard Error	25.37953652
Observations	13

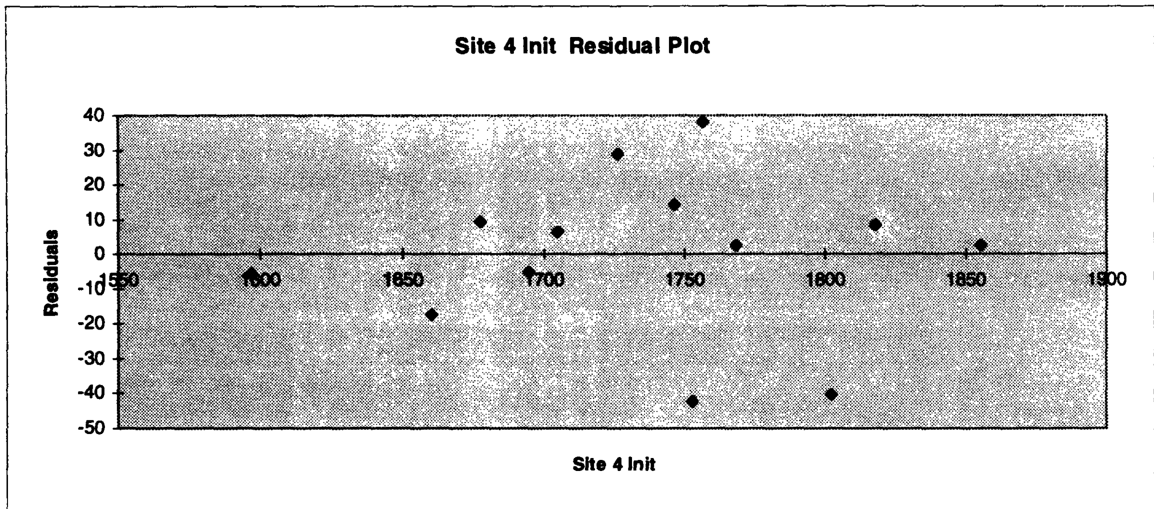
ANOVA

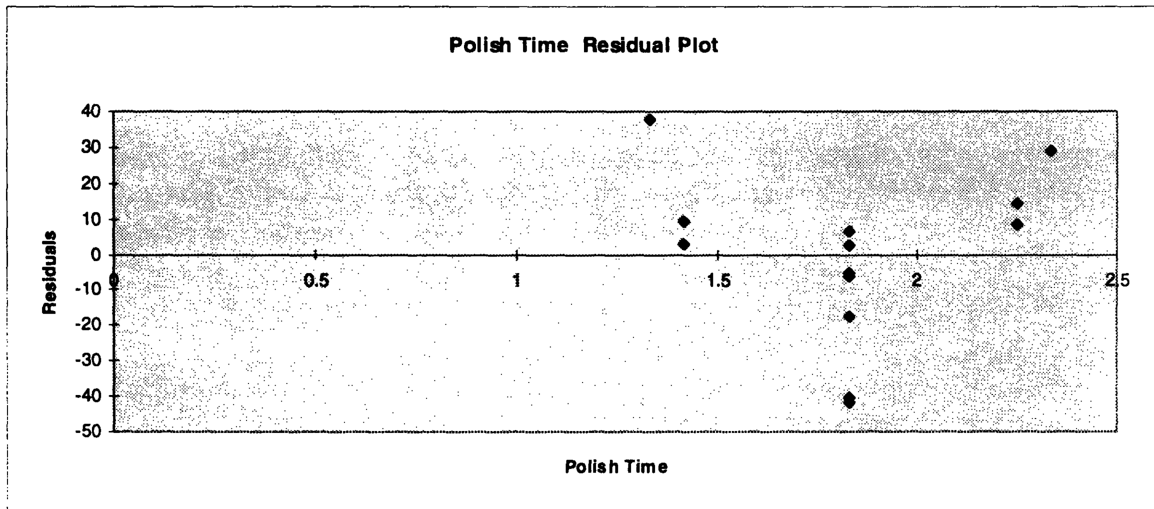
	df	SS	MS	F	Significance F
Regression	2	121330.5143	60665.25717	94.183032	3.25584E-07
Residual	10	6441.208741	644.1208741		
Total	12	127771.7231			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1552.775503	187.2338866	8.293239708	8.579E-06	1135.592333	1969.9587
Polish Time	-312.1295494	23.22262564	-13.44075189	9.991E-08	-363.8727928	-260.3863
Site 4 Init	0.281221873	0.104813537	2.683068237	0.0229714	0.047682718	0.514761

RESIDUAL OUTPUT

Observation	Predicted Site 4 Final	Residuals	Standard Residuals
1	1429.621204	-5.921203975	-0.23330623
2	1582.257299	9.242700741	0.364179256
3	1487.356054	-40.25605444	-1.586161922
4	1459.936922	6.56307815	0.258597242
5	1630.597112	37.90288827	1.493442886
6	1457.068459	-5.268458749	-0.207586878
7	1473.576183	-41.97618268	-1.65393811
8	1477.850755	2.64924486	0.104385076
9	1341.666139	14.23386059	0.560840052
10	1361.745381	8.554618883	0.337067577
11	1309.974662	28.9253382	1.139711049
12	1447.422549	-17.42254852	-0.686480169
13	1632.427281	2.772718655	0.109250169


Site 4 Init Residual Plot
Residuals
40
30
20
10
0
-10
-20
-30
-40
-50
1550
1600
1650
1700
1750
1800
1850
1900
Site 4 Init


Polish Time Residual Plot
Residuals
40
30
20
10
0
-10
-20
-30
-40
-50
0
0.5
1
1.5
2
2.5
Polish Time

Site 5 First Order Model Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.968246837
R Square	0.937501938
Adjusted R Square	0.91666925
Standard Error	30.52039772
Observations	13

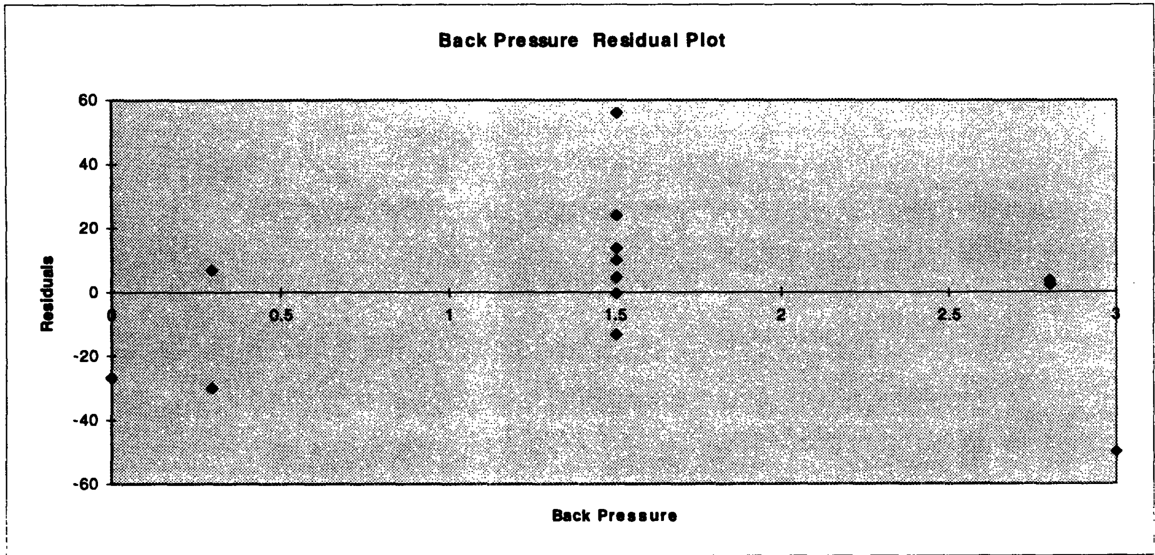
ANOVA

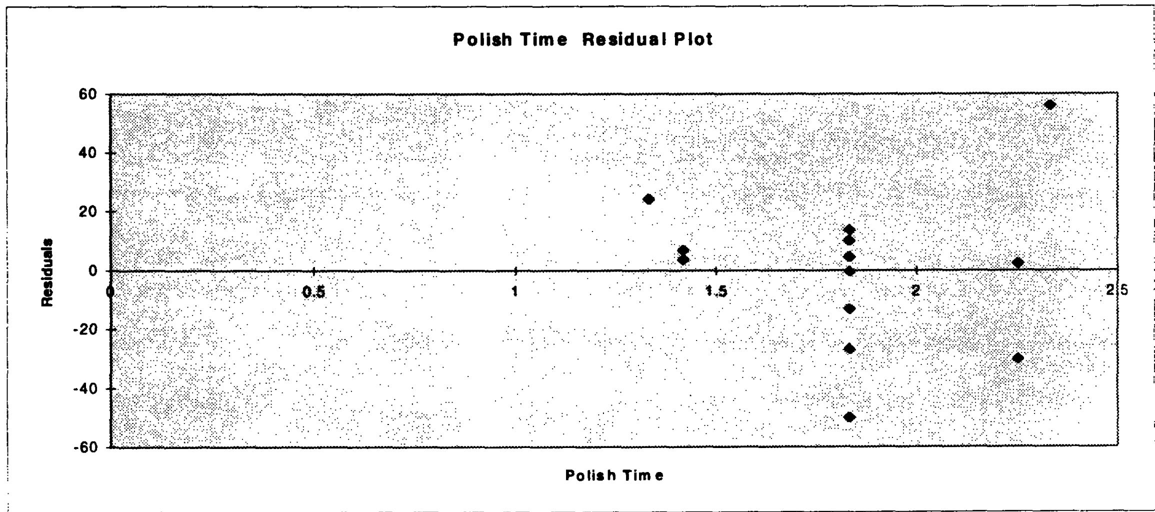
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	125755.9402	41918.64674	45.00149	9.61116E-06
Residual	9	8383.452092	931.4946769		
Total	12	134139.3923			

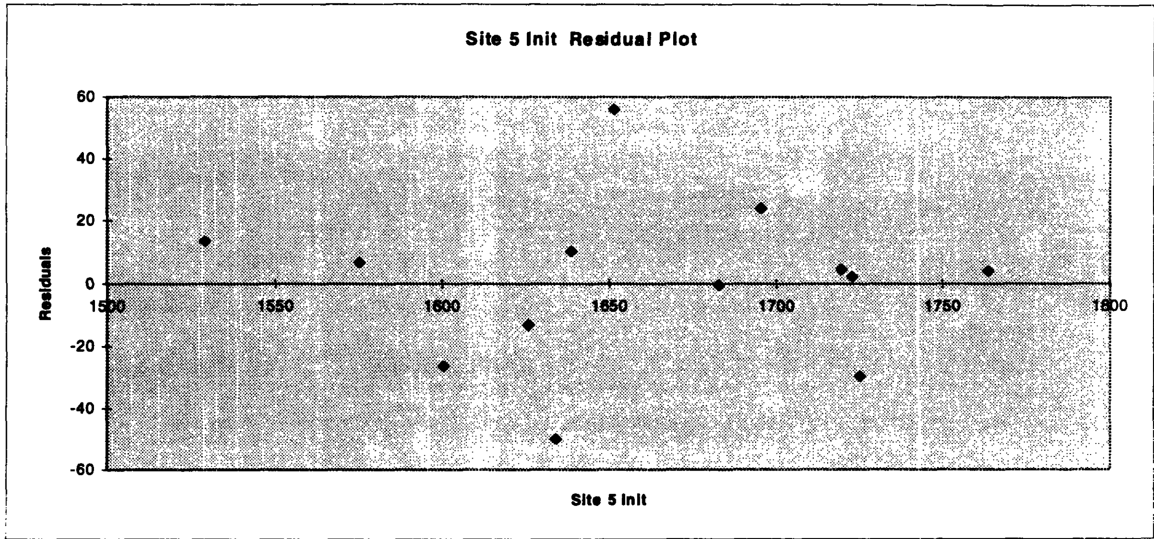
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	938.7697838	231.0304097	4.063403537	0.002827	416.1422894	1461.39728
Polish Time	-309.764972	28.06449639	-11.03761022	1.56E-06	-373.251322	-246.27862
Back Pressure	-7.783686851	10.06760827	-0.773141609	0.459262	-30.5582164	14.9908427
Site 5 Init	0.646974739	0.142041674	4.554823379	0.001376	0.325653903	0.96829558

RESIDUAL OUTPUT

Observation	*Predicted Site 5 Final*	*Residuals*	*Standard Residuals*
1	1348.545576	13.45442409	0.440833839
2	1516.780274	6.719726051	0.220171641
3	1447.791501	-0.591500889	-0.019380511
4	1419.259915	10.04008511	0.328963115
5	1611.084659	24.11534149	0.790138507
6	1410.978638	-13.37863823	-0.438350717
7	1404.802393	-50.20239324	-1.644880047
8	1471.923659	4.476341342	0.146667202
9	1334.741749	2.058250905	0.067438535
10	1355.624311	-29.82431065	-0.977192726
11	1272.594008	56.00599194	1.8350348
12	1406.156313	-26.65631266	-0.873393358
13	1619.017005	3.782994748	0.12394972


Back Pressure Residual Plot
60
40
20
0
-20
-40
-60
0
0.5
1
1.5
2
2.5
3
Residuals
Back Pressure


Polish Time Residual Plot
60
40
20
0
-20
-40
-60
0
0.5
1
1.5
2
2.5
Residuals
Polish Time


Site 5 Init Residual Plot
Residuals
60
40
20
0
-20
-40
-60
1500
1550
1600
1650
1700
1750
1800
Site 5 Init

Site 7 First Order Model Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.976311685
R Square	0.953184506
Adjusted R Square	0.937579342
Standard Error	26.8903676
Observations	13

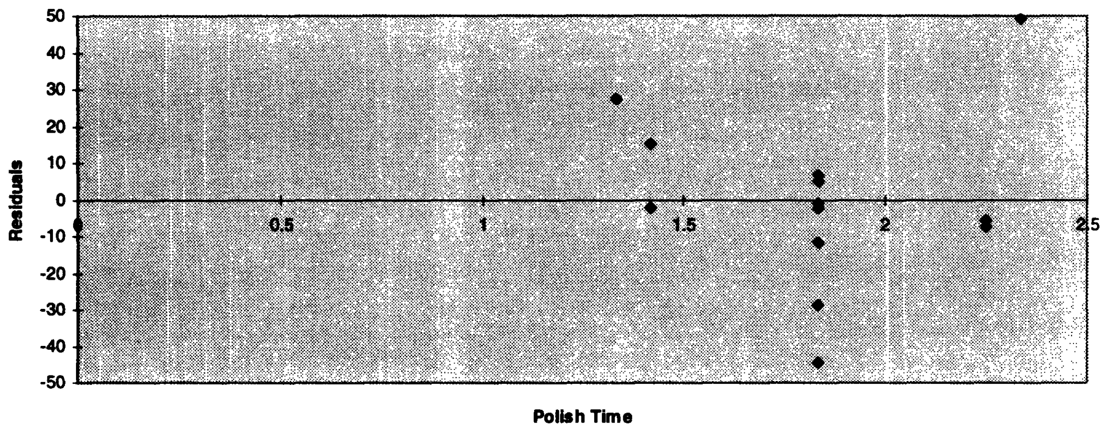
ANOVA

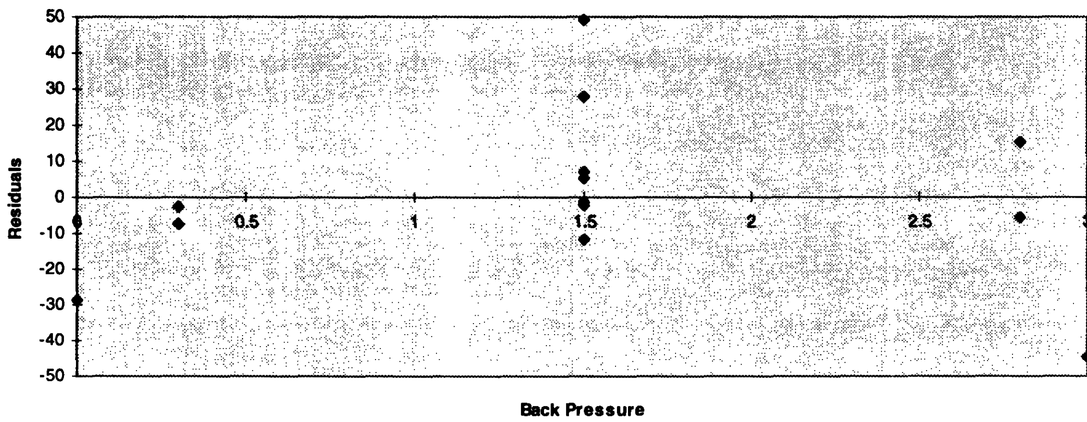
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	132502.2809	44167.42695	61.08135	2.63663E-06
Residual	9	6507.826828	723.0918698		
Total	12	139010.1077			

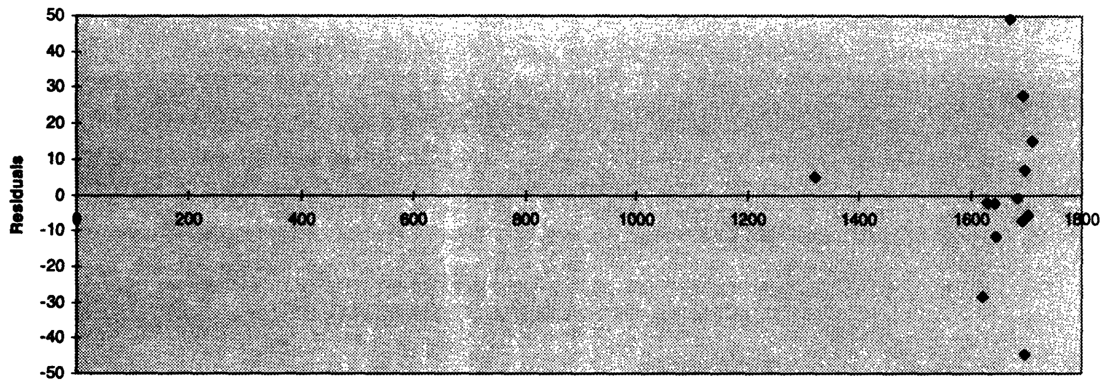
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1292.257431	133.2629559	9.697049133	4.62E-06	990.795451	1593.71941
Polish Time	-305.0531852	24.60709389	-12.39696108	5.83E-07	-360.7183413	-249.388029
Back Pressure	-2.250150423	8.342681038	-0.269715504	0.793461	-21.12262047	16.6223196
Site 7 Init	0.430719457	0.077429859	5.562704946	0.000351	0.255560815	0.6058781

RESIDUAL OUTPUT

Observation	*Predicted Site 7 Final*	*Residuals*	*Standard Residuals*
1	1299.072227	5.027773148	0.186973017
2	1567.397279	-2.497278637	-0.092868892
3	1460.721239	6.778760849	0.252088813
4	1431.690748	-2.190747733	-0.081469609
5	1612.084889	27.61511079	1.026951777
6	1438.539187	-11.5391871	-0.429119723
7	1457.04451	-44.6445099	-1.66024171
8	1454.99267	-1.09267037	-0.040634267
9	1333.102579	-5.70257873	-0.212067712
10	1334.2054	-7.305400487	-0.271673508
11	1296.995941	49.00405933	1.822364798
12	1432.309369	-28.60936884	-1.063926283
13	1590.543962	15.15603768	0.563623298


Polish Time Residual Plot
50
40
30
20
10
0
-10
-20
-30
-40
-50
Residuals
0.5
1
1.5
2
2.5
Polish Time


Back Pressure Residual Plot
50
40
30
20
10
0
-10
-20
-30
-40
-50
Residuals
0.5
1
1.5
2
2.5
3
Back Pressure


Site 7 Init Residual Plot
Residuals
50
40
30
20
10
0
-10
-20
-30
-40
-50
0
200
400
600
800
1000
1200
1400
1600
1800
Site 7 Init

Site 8 First Order Model Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.973917782
R Square	0.948515846
Adjusted R Square	0.938219015
Standard Error	27.85761022
Observations	13

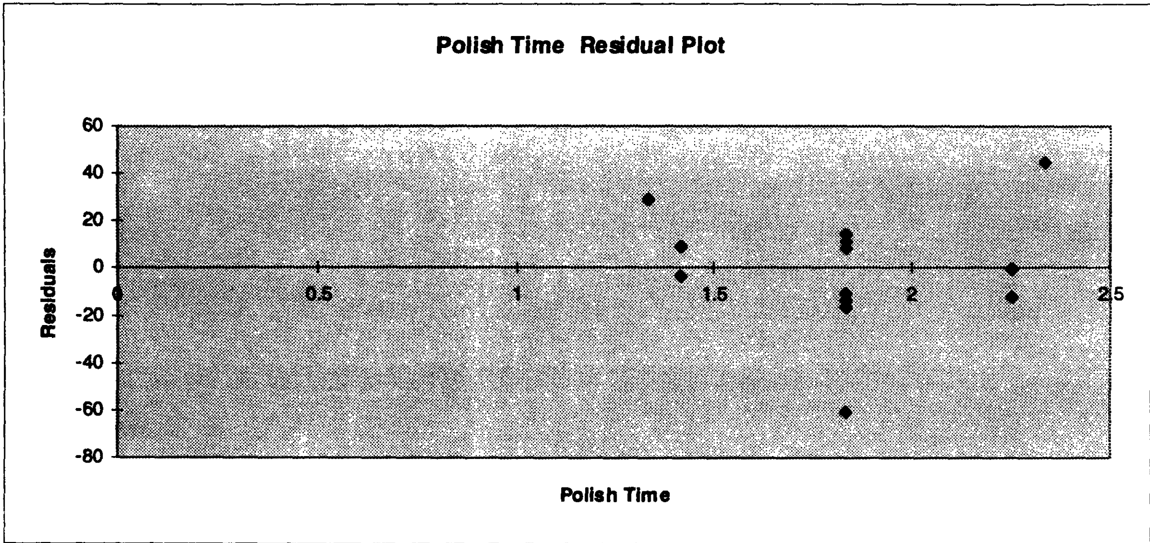
ANOVA

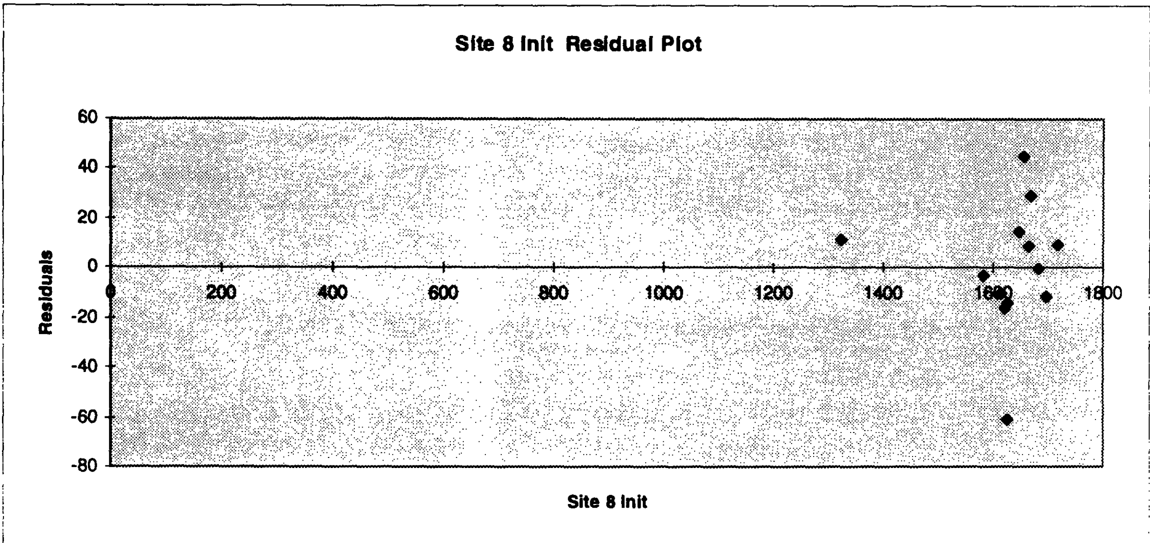
	df	SS	MS	F	Significance F
Regression	2	142974.5448	71487.27238	92.11726	3.61716E-07
Residual	10	7760.464473	776.0464473		
Total	12	150735.0092			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1199.754728	139.206679	8.618514114	6.1E-06	889.5828643	1509.92659
Polish Time	-322.48943	25.55549325	-12.61918237	1.82E-07	-379.430627	-265.548233
Site 8 Init	0.486808465	0.082612972	5.892639513	0.000153	0.30273526	0.67088167

RESIDUAL OUTPUT

Observation	Predicted Site 8 Final	Residuals	Standard Residuals
1	1252.961153	11.23884723	0.403439029
2	1513.561184	-3.261183654	-0.117066167
3	1419.449648	8.450352082	0.303340883
4	1400.464118	-13.96411777	-0.501267613
5	1581.765342	29.33465847	1.053021355
6	1397.348544	-16.44854359	-0.590450633
7	1400.464118	-60.76411777	-2.181239427
8	1410.248968	14.35103208	0.515156611
9	1293.403477	-0.403476855	-0.014483542
10	1300.072753	-11.87275283	-0.426194233
11	1252.703997	44.59600272	1.600855291
12	1395.255267	-10.55526719	-0.37890067
13	1578.501433	9.298567069	0.333789115


Polish Time Residual Plot
60
40
20
0
-20
-40
-60
-80
Residuals
0
0.5
1
1.5
2
2.5
Polish Time


Site 8 Init Residual Plot
60
40
20
0
-20
-40
-60
-80
Residuals
0
200
400
600
800
1000
1200
1400
1600
1800
Site 8 Init

Data and Regression Results of Experiment #2

Polish Time	Back Pressure	Site 1 Init	Site 2 Init	Site 3 Init	Site 4 Init	Site 5 Init	Site 6 Init	Site 7 Init	Site 8 Init	Site 9 Init
1.83333	0	1538.9	1806.9	1668.1	1746.9	1706.9	1753.5	1755.9	1613.9	1402.2
1.32	1.5	1481.8	1754.2	1734.9	1792.2	1707.4	1725.7	1711.5	1640.0	1451.6
1.83333	1.5	1544.4	1779.6	1705.4	1796.9	1689.3	1725.1	1843.9	1668.2	1552.7
1.41666	0.3	1547.3	1777.2	1715.3	1829.6	1716.8	1708.8	1881.3	1661.1	1512
2.25	2.7	1506	1712.2	1680.3	1796.6	1725.4	1650.9	1824.1	1631.7	1487.2
1.83333	1.5	1476	1644.3	1717.2	1843	1741.7	1699.8	1868.2	1648	1502.3
1.83333	3	1584.1	1808.3	1722.1	1848.9	1785	1724.3	1938.3	1722.5	1604.5
1.41666	2.7	1596.8	1837.3	1758.3	1878.1	1808.8	1776.7	1922.2	1718.2	1541.5
1.83333	1.5	1509.7	1733.8	1693.7	1748.1	1652.1	1667.3	1829.9	1604.3	1483.2
2.33333	1.5	1570.8	1824.8	1722.5	1815.3	1747.1	1711.6	1886.4	1702	1549.9
2.25	0.3	1662.4	1898.8	1856.8	1936.7	1866.1	1824.2	1970.3	1793.9	1594.9
1.83333	1.5	1591.6	1846.1	1742.6	1866.9	1760.9	1779.5	1857.3	1694.5	1540.6
1.83333	1.5	1482.8	1646	1582.2	1621.2	1577	1601.2	1603.4	1515	1365.2
1.83333	1.5	1410.4	1542.2	1573.7	1620.3	1548.4	1545	1569.5	1475.5	1330.8
		Site 1 Final	**Site 2 Final**	**Site 3 Final**	**Site 4 Final**	**Site 5 Final**	**Site 6 Final**	**Site 7 Final**	**Site 8 Final**	**Site 9 Final**
		1279.4	1392.1	1381	1360.3	1495.6	1280.7	1407.1	1429.3	1187.8
		1513	1617.3	1621.3	1632.6	1706.4	1561.4	1631.7	1662.1	1489.8
		1289.3	1408.9	1400.2	1395.5	1479.7	1282.5	1421	1437.1	1238.1
		1465.7	1530	1539.6	1555.5	1608.3	1466.5	1573.8	1575.3	1424.6
		1046.3	1148.6	1221.7	1212.5	1342.7	1088.3	1232.4	1267.2	1028.3
		1305.9	1387.4	1401.9	1384.5	1508.9	1271.8	1453.3	1467.3	1213.8
		1242.4	1342.2	1403.3	1394.6	1480.9	1325.5	1426.4	1444.1	1236.8
		1477.4	1538.4	1587.1	1608	1657.6	1501.8	1615.9	1620.2	1474.9
		1286.7	1382.4	1400	1371.8	1483.5	1293.3	1445.7	1437.8	1198.5
		1079.8	1182.6	1166.3	1197.2	1344.6	1061.5	1235.3	1278.2	957.06
		1135.8	1188.4	1201.9	1200.4	1387.5	1075.8	1279.4	1319.9	1005.3
		1248.6	1346	1418.1	1416	1496.4	1293.3	1435.6	1443.3	1274.2
		1236.7	1325.3	1327.1	1302.6	1441	1258.7	1356.4	1387.6	1106.3
		1137.9	1291.5	1279.8	1271	1355.7	1176.4	1261.3	1312.9	1108.1

Site 1 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.966884202
R Square	0.93486506
Adjusted R Square	0.923022344
Standard Error	39.71035247
Observations	14

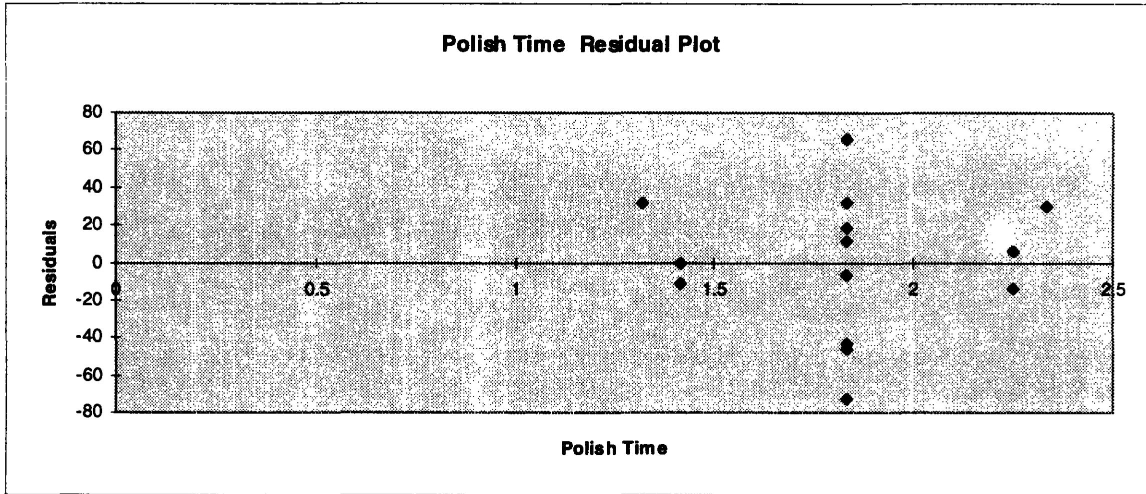
ANOVA

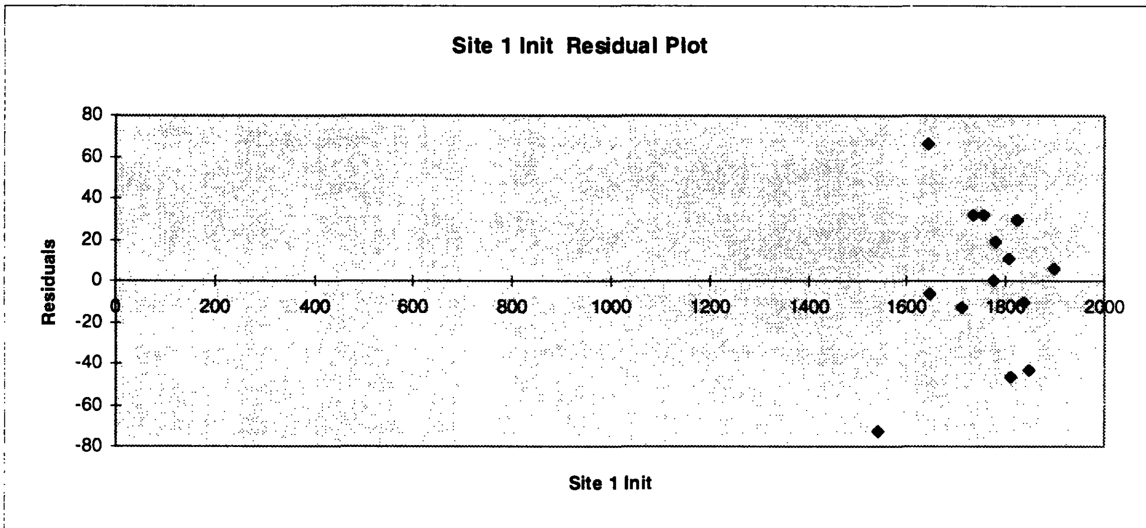
	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	248963.156	124481.5781	78.9401	2.9921E-07
Residual	11	17346.0330	1576.912093		
Total	13	266309.189			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1428.36227	264.714133	5.395867049	0.00022	845.730096	2010.9944
Polish Time	-465.1496743	37.0237900	-12.56353479	7.25E-08	-546.63853	-383.6608
Site 1 Init	0.450190868	0.1763683	2.552561164	0.026872	0.06200667	0.8383751

RESIDUAL OUTPUT

Observation	*Predicted Site 1 Final*	*Residuals*	*Standard Residuals*
1	1268.388143	11.0118566	0.27730443
2	1481.457527	31.54247	0.794313597
3	1270.864193	18.4358069	0.464256944
4	1465.980405	-0.28040537	-0.007061266
5	1059.762949	-13.4629490	-0.339028697
6	1240.071138	65.8288622	1.657725458
7	1288.736771	-46.3367706	-1.166868781
8	1488.264853	-10.8648533	-0.273602541
9	1255.24257	31.45743	0.792172016
10	1050.174395	29.6256051	0.746042361
11	1130.172801	5.62719926	0.141706102
12	1292.113202	-43.513202	-1.095764691
13	1243.132436	-6.4324357	-0.161983848
14	1210.538617	-72.638617	-1.829211084


Polish Time Residual Plot
80
60
40
20
0
-20
-40
-60
-80
Residuals
0
0.5
1
1.5
2
2.5
Polish Time


Site 1 Init Residual Plot
80
60
40
20
0
-20
-40
-60
-80
Residuals
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Site 1 Init

Site 2 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.968931923
R Square	0.938829071
Adjusted R Square	0.933731493
Standard Error	35.23150647
Observations	14

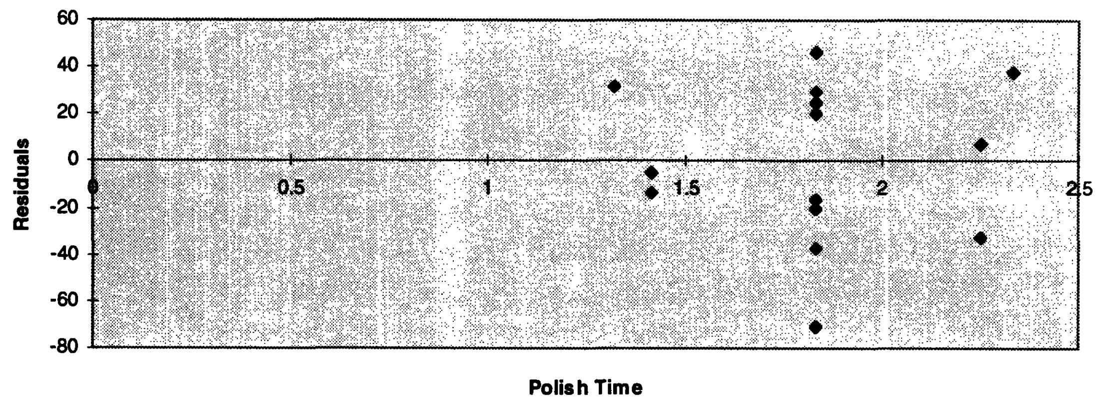
ANOVA

	df	SS	MS	F	Significance F
Regression	1	228604.6836	228604.6836	184.17162	1.21419E-08
Residual	12	14895.10858	1241.259048		
Total	13	243499.7921			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	2160.077083	59.48857859	36.31078661	1.219E-13	2030.462607	2289.691559
Polish Time	-435.0308702	32.05595559	-13.57098431	1.214E-08	-504.8747963	-365.186944

RESIDUAL
OUTPUT

Observation	Predicted Site 2 Final	Residuals	Standard Residuals
1	1362.521938	29.57806222	0.839534416
2	1585.836334	31.46366562	0.89305479
3	1362.521938	46.37806222	1.316380333
4	1543.783205	-13.78320525	-0.391218163
5	1181.257625	-32.65762509	-0.92694376
6	1362.521938	24.87806222	0.706131094
7	1362.521938	-20.32193778	-0.576811491
8	1543.783205	-5.383205255	-0.152795205
9	1362.521938	19.87806222	0.564212667
10	1145.006503	37.59349732	1.067042006
11	1181.257625	7.142374909	0.202726923
12	1362.521938	-16.52193778	-0.468953486
13	1362.521938	-37.22193778	-1.056495776
14	1362.521938	-71.02193778	-2.015864347


Polish Time Residual Plot
60
40
20
0
-20
-40
-60
-80
Residuals
0
0.5
1
1.5
2
2.5
Polish Time

Site 3 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.980185592
R Square	0.960763795
Adjusted R Square	0.953629939
Standard Error	29.56746848
Observations	14

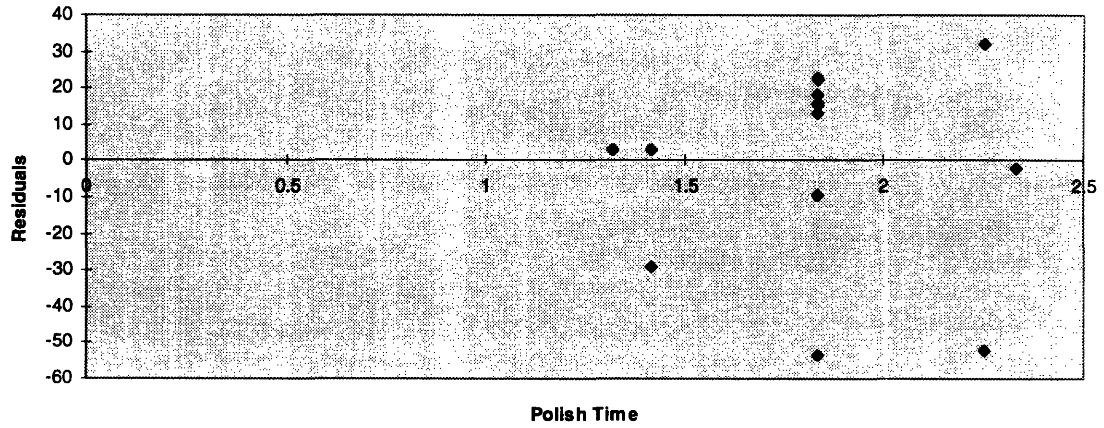
ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	235478.1422	117739.0711	134.676655	1.84195E-08
Residual	11	9616.587118	874.2351926		
Total	13	245094.7293			

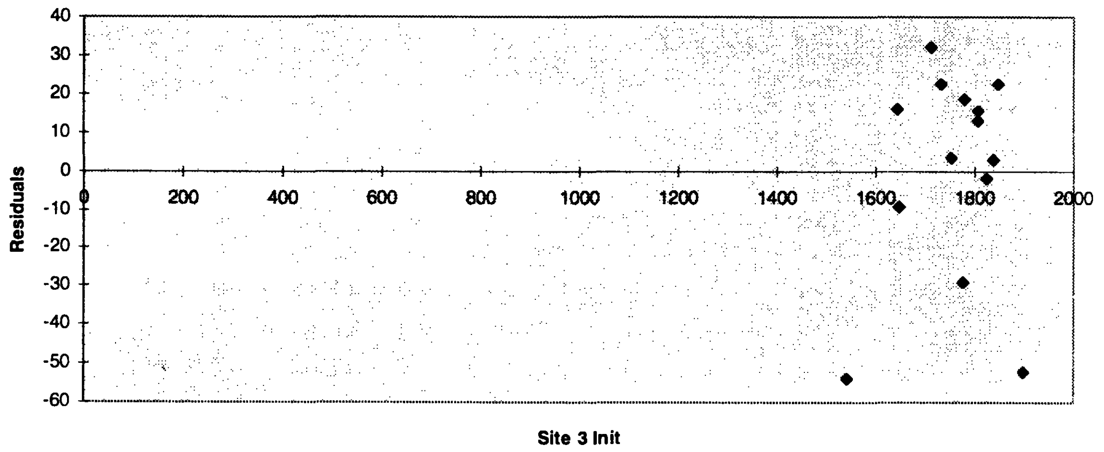
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1562.724718	203.3346297	7.685482399	9.545E-06	1115.187989	2010.261446
Polish Time	-439.5290389	26.97193773	-16.29579021	4.7501E-09	-498.8939036	-380.1641742
Site 3 Init	0.366375796	0.117671506	3.113547262	0.00986286	0.107382426	0.625369165

RESIDUAL OUTPUT

Observation	*Predicted Site 3 Final*	*Residuals*	*Std Residuals*
1	1368.074409	12.92559069	0.437155812
2	1618.171754	3.128246	0.105800265
3	1381.740226	18.45977351	0.624327156
4	1568.502835	-28.9028348	-0.977521455
5	1189.405629	32.29437063	1.092226433
6	1386.063461	15.83653913	0.535606866
7	1387.858702	15.44129773	0.522239425
8	1584.256994	2.843005987	0.096153176
9	1377.45363	22.54637032	0.76253976
10	1168.240733	-1.940733135	-0.065637447
11	1254.070957	-52.17095729	-1.764471562
12	1395.369406	22.73059392	0.768770378
13	1336.602728	-9.50272847	-0.321391345
14	1333.488534	-53.68853421	-1.815797461



Polish Time Residual Plot
Residuals
40
30
20
10
0
-10
-20
-30
-40
-50
-60
0
0.5
1
1.5
2
2.5
Polish Time



Site 3 Init Residual Plot
Residuals
40
30
20
10
0
-10
-20
-30
-40
-50
-60
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Site 3 Init

Site 4 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.985823138
R Square	0.971847259
Adjusted R Square	0.966728579
Standard Error	25.81544408
Observations	14

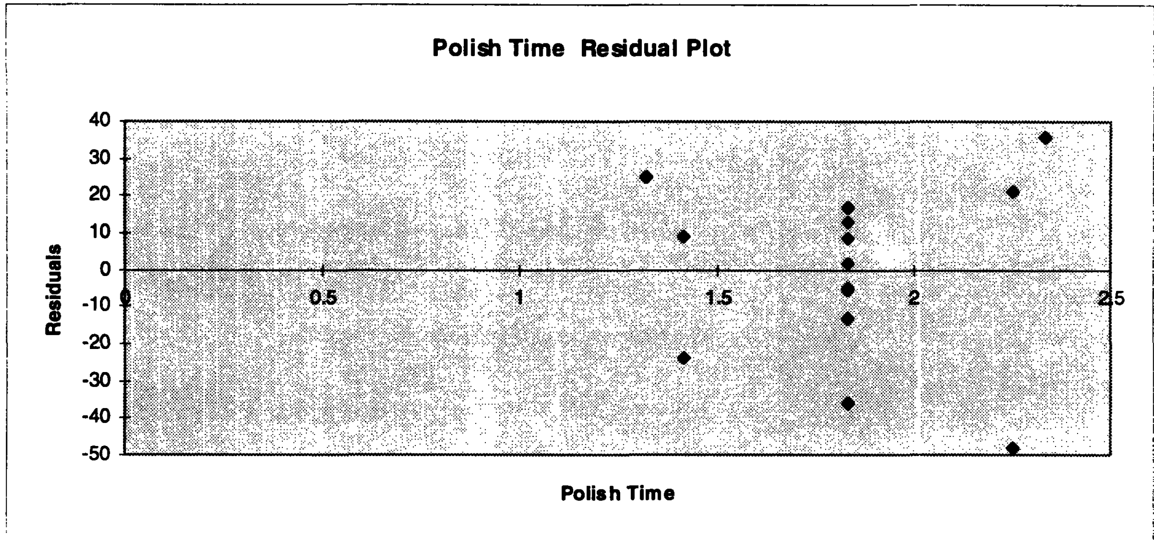
ANOVA

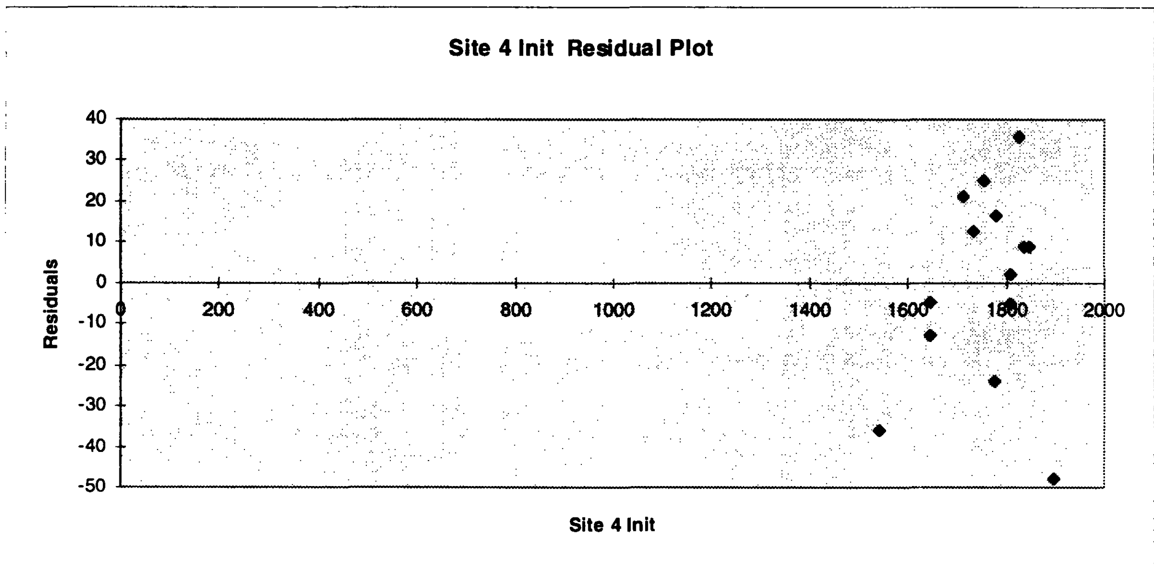
	df	SS	MS	F	Significance F
Regression	2	253063.3263	126531.6632	189.862859	2.96732E-09
Residual	11	7330.808684	666.4371531		
Total	13	260394.135			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1472.53052	147.7543925	9.96606933	7.6483E-07	1147.32513	1797.735909
Polish Time	-449.427776	23.53498346	-19.09615857	8.7721E-10	-501.2279516	-397.627601
Site 4 Init	0.406368164	0.080124383	5.071716594	0.00035962	0.230015496	0.582720831

RESIDUAL OUTPUT

Observation	Predicted Site 4 Final	Residuals	Standard Residuals
1	1358.46564	1.834360069	0.071056692
2	1607.578878	25.02112198	0.969230741
3	1378.784048	16.71595189	0.647517503
4	1579.332213	-23.83221251	-0.923176546
5	1191.399066	21.10093378	0.817376363
6	1397.51762	-13.01762045	-0.50425708
7	1399.915193	-5.315192615	-0.205891969
8	1599.041068	8.958931559	0.34703767
9	1358.953282	12.84671827	0.497636927
10	1161.547334	35.6526657	1.381059555
11	1248.331246	-47.93124593	-1.856688802
12	1407.22982	8.77018044	0.339726112
13	1307.385162	-4.78516177	-0.185360428
14	1307.01943	-36.01943042	-1.395266737


Polish Time Residual Plot
Residuals
40
30
20
10
0
-10
-20
-30
-40
-50
0
0.5
1
1.5
2
2.5
Polish Time


Site 4 Init Residual Plot
Residuals
40
30
20
10
0
-10
-20
-30
-40
-50
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Site 4 Init

Site 5 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.971164873
R Square	0.943161211
Adjusted R Square	0.932826886
Standard Error	29.02100013
Observations	14

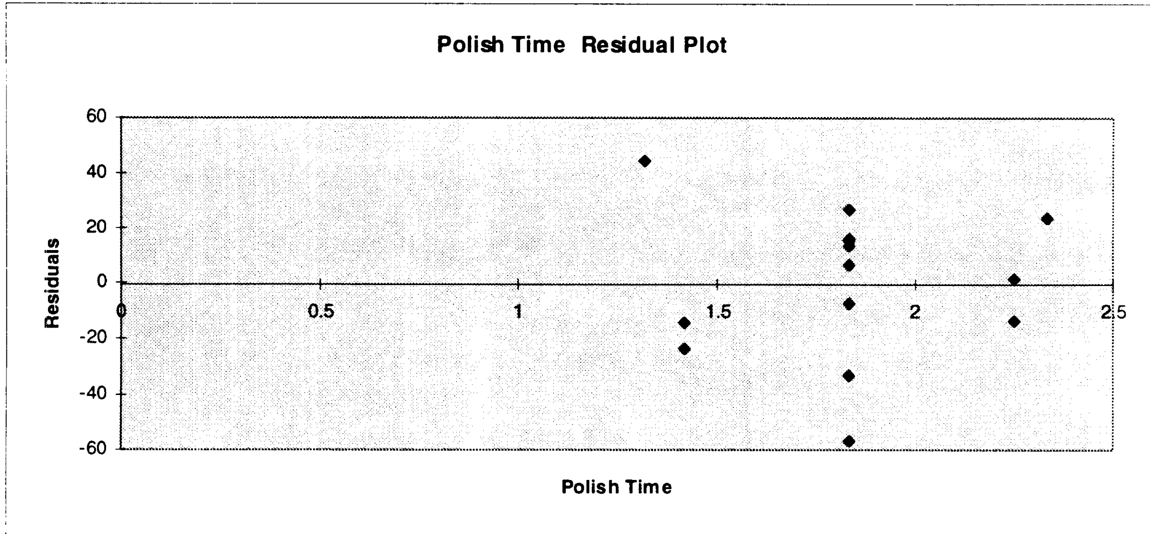
ANOVA

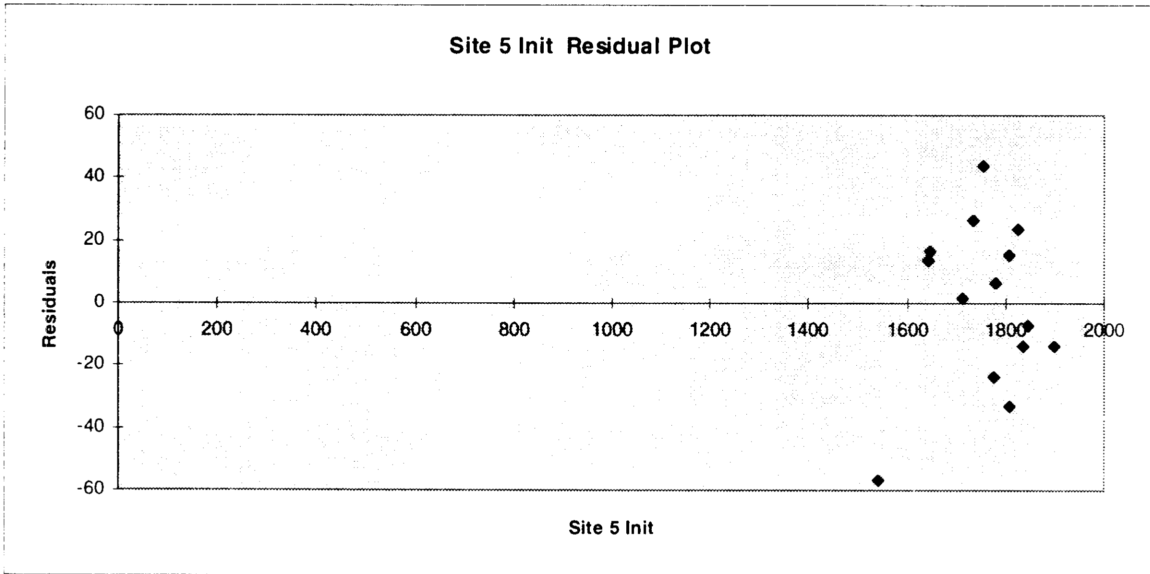
	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	153729.9742	76864.9871	91.264905	1.41432E-07
Residual	11	9264.402935	842.2184486		
Total	13	162994.3771			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1397.518271	166.3658764	8.400269942	4.094E-06	1031.34926	1763.687281
Polish Time	-353.8168827	26.67665915	-13.26316316	4.132E-08	-412.5318433	-295.1019221
Site 5 Init	0.428583994	0.096666341	4.433642473	0.0010055	0.215822705	0.641345283

RESIDUAL OUTPUT

Observation	*Predicted Site 5 Final*	*Residuals*	*Standard Residuals*
1	1480.405184	15.194816	0.523580026
2	1662.244296	44.15570359	1.52150868
3	1472.862106	6.837894288	0.235618837
4	1632.070569	-23.77056935	-0.819081673
5	1340.909107	1.790892637	0.061710232
6	1495.319907	13.58009301	0.467940214
7	1513.877594	-32.97759392	-1.136335542
8	1671.500297	-13.90029677	-0.478973733
9	1456.918781	26.58121886	0.915930489
10	1320.725819	23.87418081	0.822651897
11	1401.210875	-13.71087529	-0.472446684
12	1503.54872	-7.148719666	-0.246329197
13	1424.732123	16.26787679	0.560555347
14	1412.474621	-56.77462099	-1.956328891


Polish Time Residual Plot
60
40
20
0
-20
-40
-60
Residuals
0
0.5
1
1.5
2
2.5
Polish Time


Site 5 Init Residual Plot
60
40
20
0
-20
-40
-60
Residuals
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Site 5 Init

Site 6 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.989925421
R Square	0.979952339
Adjusted R Square	0.97393804
Standard Error	24.64699256
Observations	14

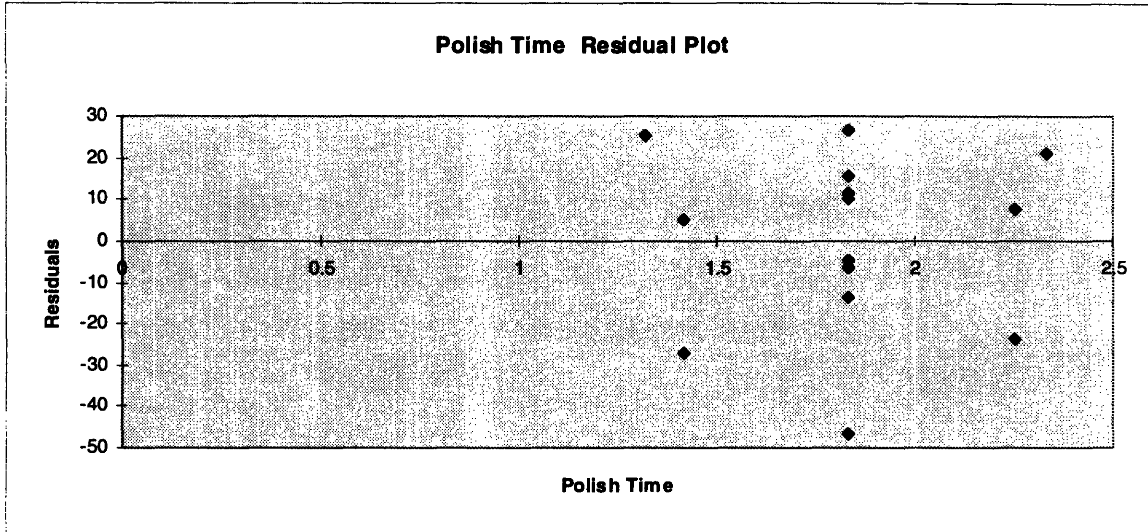
ANOVA

	df	SS	MS	F	Significance F
Regression	3	296940.2726	98980.09086	162.9371	8.69267E-09
Residual	10	6074.742421	607.4742421		
Total	13	303015.015			

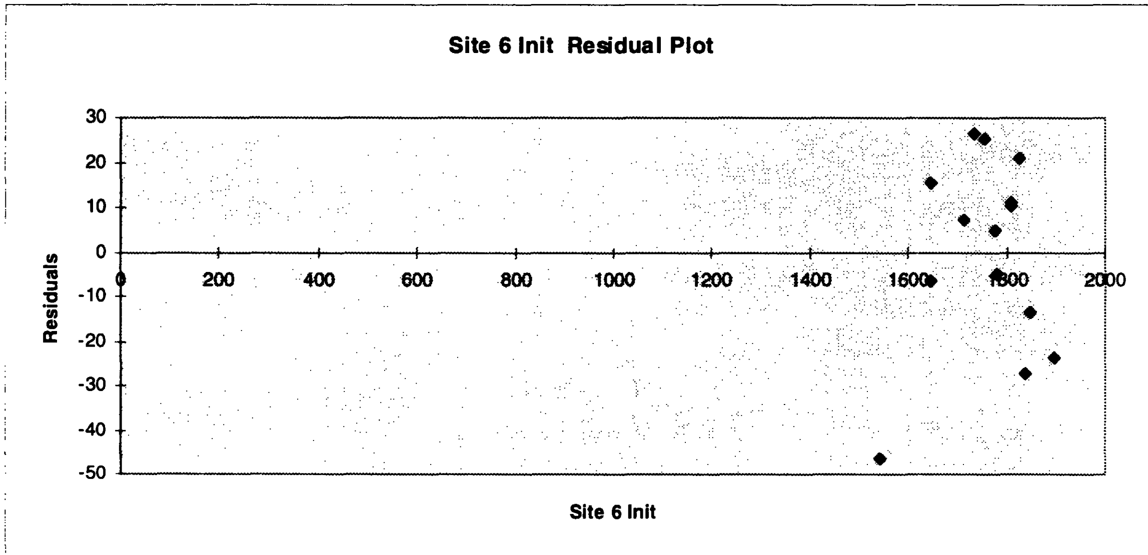
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1531.480463	172.9345373	8.85583925	4.78E-06	1146.158235	1916.802691
Polish Time	-483.9748006	22.44441799	-21.56325911	1.03E-09	-533.984089	-433.9655122
Site 6 Init	0.357121266	0.09573061	3.730481448	0.003907	0.143820137	0.570422395
Back Pressure	18.06731083	7.856989027	2.299520945	0.04429	0.560845295	35.57377637

RESIDUAL OUTPUT

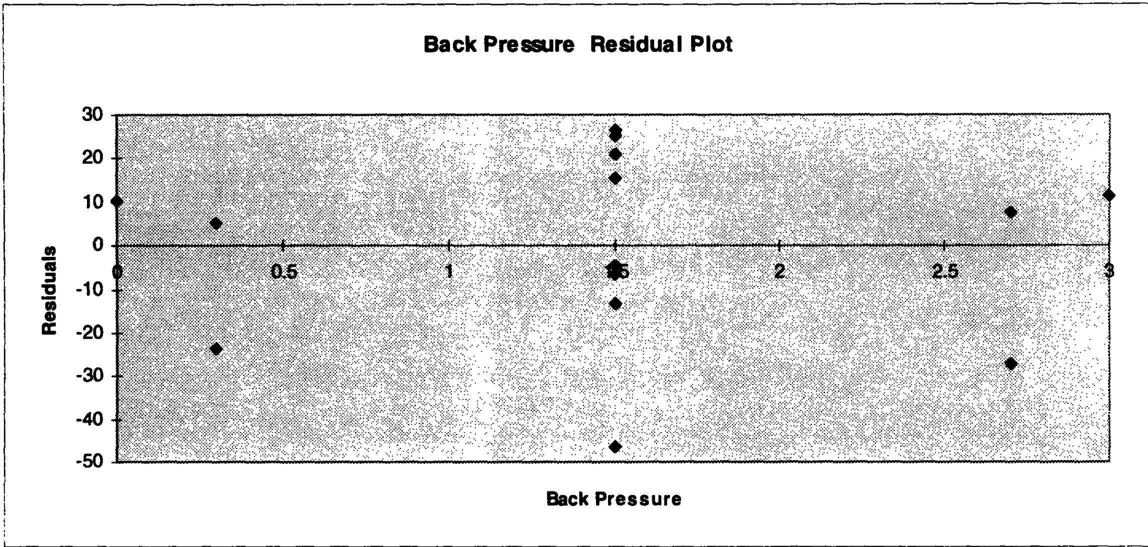
Observation	Pred. Site 6 Final	Residuals	Standard Residuals
1	1270.407082	10.29291845	0.417613566
2	1536.018861	25.38113898	1.029786451
3	1287.365804	-4.86580385	-0.19741978
4	1461.518347	4.98165343	0.202120134
5	1080.890399	7.409601257	0.300629022
6	1278.330636	-6.530635823	-0.264966844
7	1314.181073	11.31892691	0.459241706
8	1529.128427	-27.32842653	-1.108793556
9	1266.724195	26.57580532	1.07825753
10	1040.557266	20.94273355	0.849707465
11	1099.417968	-23.61796812	-0.958249493
12	1306.793201	-13.49320071	-0.547458303
13	1243.118479	15.58152099	0.632187516
14	1223.048264	-46.64826386	-1.892655412



Polish Time Residual Plot
30
20
10
0
-10
-20
-30
-40
-50
Residuals
0
0.5
1
1.5
2
2.5
Polish Time



Site 6 Init Residual Plot
30
20
10
0
-10
-20
-30
-40
-50
Residuals
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Site 6 Init


Back Pressure Residual Plot
Residuals
30
20
10
0
-10
-20
-30
-40
-50
0
0.5
1
1.5
2
2.5
3
Back Pressure

Site 7 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.977101632
R Square	0.9547276
Adjusted R Square	0.946496255
Standard Error	30.53822281
Observations	14

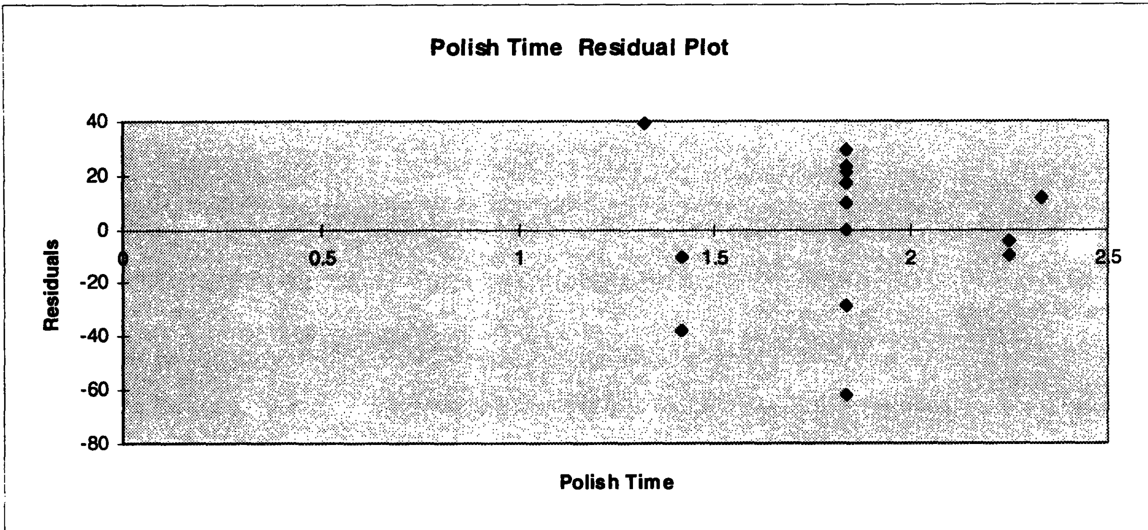
ANOVA

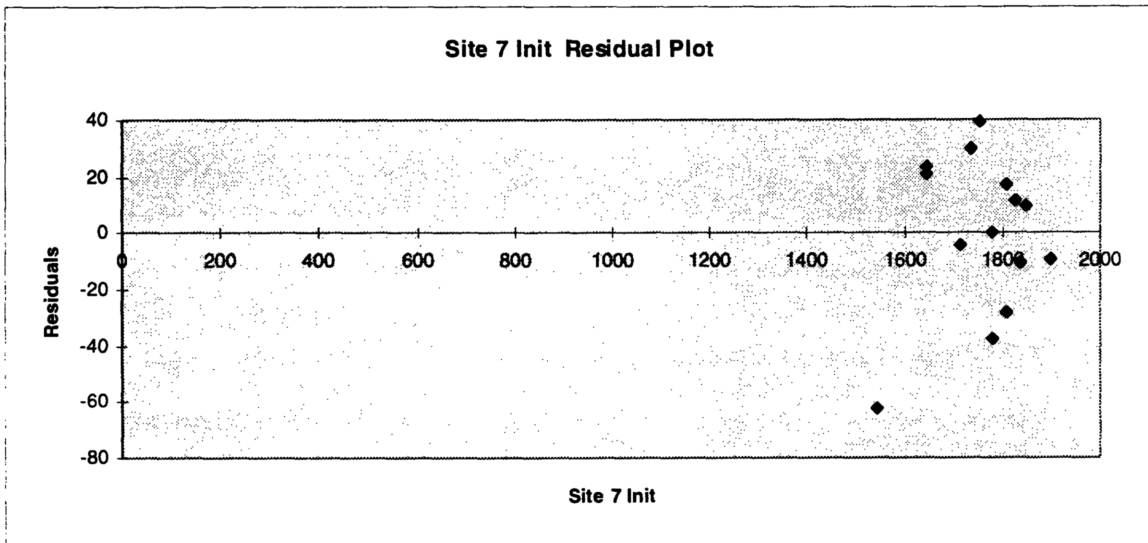
	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	216334.69	108167.345	115.9868225	4.04654E-08
Residual	11	10258.41358	932.5830526		
Total	13	226593.1036			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1544.051292	132.3719009	11.66449436	1.55609E-07	1252.702555	1835.400029
Polish Time	-425.4332714	28.24673798	-15.06132395	1.09174E-08	-487.603954	-363.2625888
Site 7 Init	0.356306641	0.072154368	4.938116011	0.000443913	0.197495867	0.515117415

RESIDUAL OUTPUT

Observation	*Predicted Site 7 Final*	*Residuals*	*Standard Residuals*
1	1389.730544	17.3694565	0.568777581
2	1592.29819	39.40181015	1.290245683
3	1421.085528	-0.08552792	-0.002800684
4	1611.673699	-37.87369946	-1.240206403
5	1236.765375	-4.365375228	-0.142947913
6	1429.743779	23.5562207	0.771368421
7	1454.720875	-28.32087484	-0.92739106
8	1626.246641	-10.34664108	-0.338809535
9	1416.097235	29.60276506	0.969367642
10	1223.511924	11.78807554	0.386010529
11	1288.857406	-9.457406155	-0.309690784
12	1425.860037	9.739963089	0.31894335
13	1335.393781	21.00621926	0.687866461
14	1323.314986	-62.0149856	-2.030733287


Polish Time Residual Plot
40
20
0
-20
-40
-60
-80
Residuals
0
0.5
1
1.5
2
2.5
Polish Time


Site 7 Init Residual Plot
40
20
0
-20
-40
-60
-80
Residuals
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Site 7 Init

Site 8 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.981757903
R Square	0.963848579
Adjusted R Square	0.957275594
Standard Error	24.98467775
Observations	14

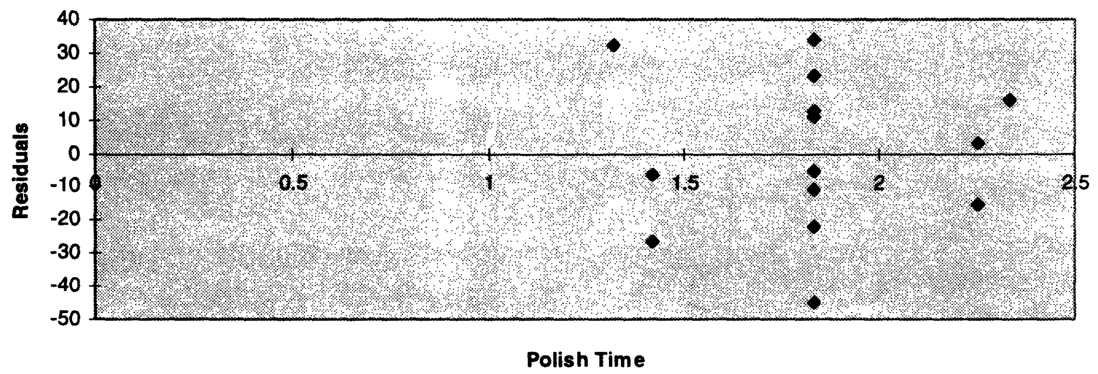
ANOVA

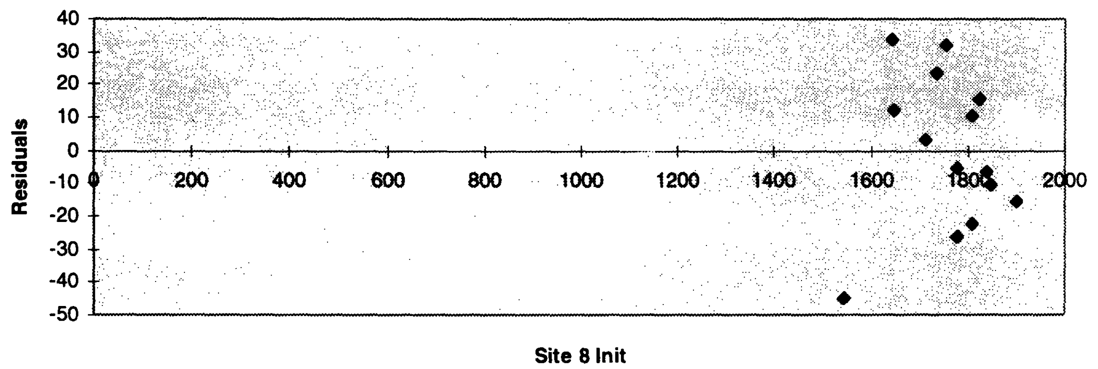
	df	SS	MS	F	Significance F
Regression	2	183072.7197	91536.35983	146.6379	1.17406E-08
Residual	11	6866.575343	624.2341221		
Total	13	189939.295			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1425.245773	140.3671973	10.15369545	6.35E-07	1116.299499	1734.192047
Polish Time	-389.5791704	23.00866417	-16.93184652	3.16E-09	-440.2209244	-338.9374164
Site 8 Init	0.438431277	0.085124749	5.150456022	0.000318	0.251072873	0.625789681

RESIDUAL OUTPUT

Observation	Predicted Site 8 Final	Residuals	Standard Residuals
1	1418.60283	10.69716952	0.428149189
2	1630.028562	32.07143767	1.28364424
3	1442.409649	-5.309648817	-0.212516202
4	1601.620013	-26.32001261	-1.053446151
5	1264.080954	3.119045704	0.12483834
6	1433.553337	33.74666298	1.350694346
7	1466.216467	-22.11646715	-0.885201217
8	1626.654439	-6.454438522	-0.258335872
9	1414.39389	23.40610978	0.936818558
10	1262.439041	15.7609592	0.630824994
11	1335.194507	-15.29450742	-0.612155481
12	1453.940391	-10.6403914	-0.425876672
13	1375.241977	12.35802281	0.494624063
14	1357.923942	-45.02394175	-1.802062136


Polish Time Residual Plot
Residuals
40
30
20
10
0
-10
-20
-30
-40
-50
0
0.5
1
1.5
2
2.5
Polish Time


Site 8 Init Residual Plot
Residuals
40
30
20
10
0
-10
-20
-30
-40
-50
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Site 8 Init

Site 9 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.986933684
R Square	0.974038096
Adjusted R Square	0.96931775
Standard Error	29.18191346
Observations	14

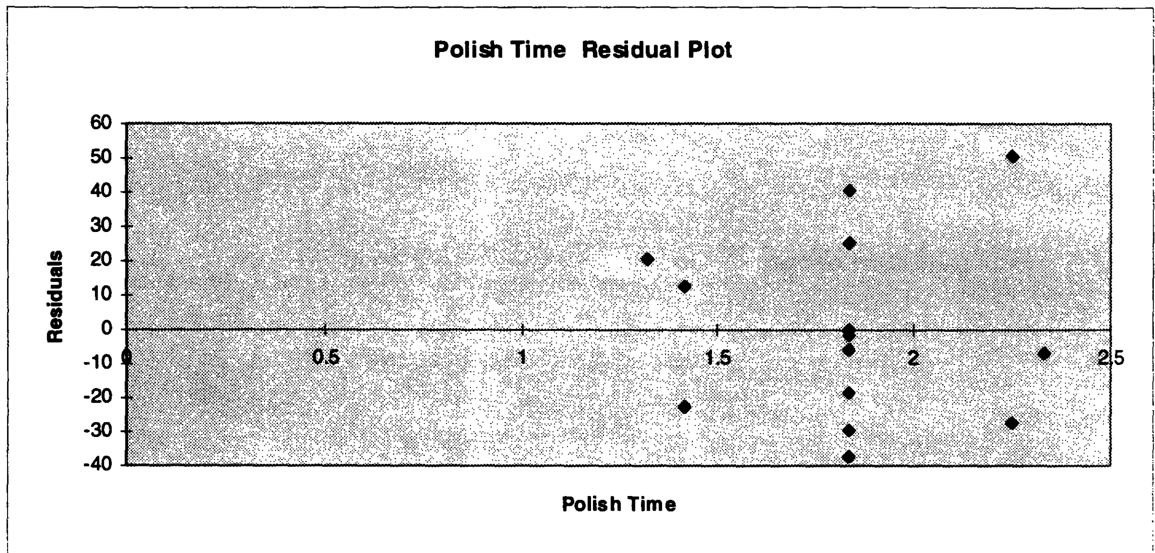
ANOVA

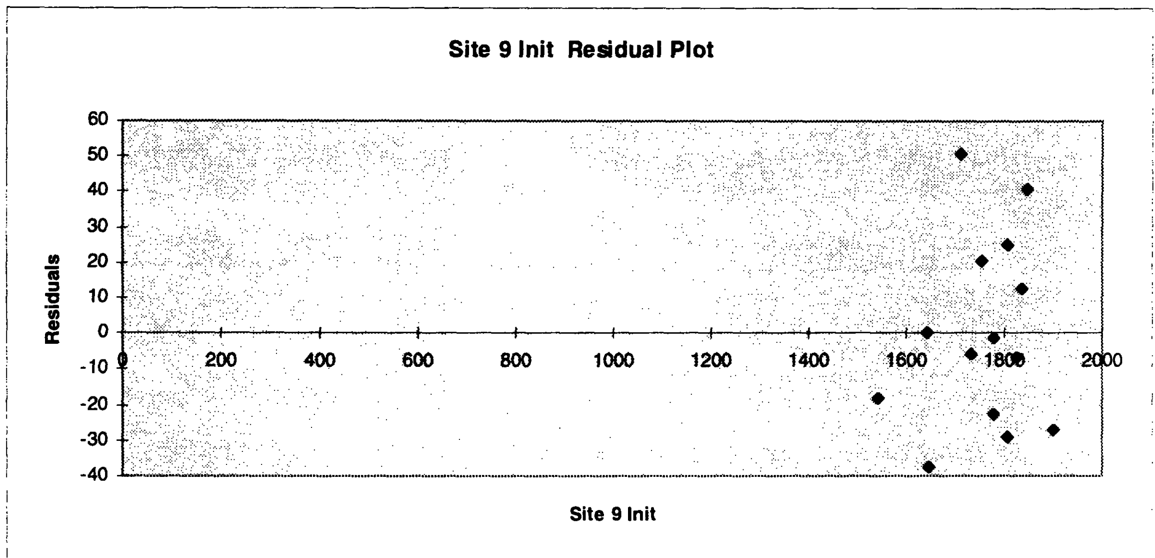
	df	SS	MS	F	Significance F
Regression	2	351446.8235	175723.4118	206.3489	1.90043E-09
Residual	11	9367.424808	851.5840734		
Total	13	360814.2483			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	1452.418291	149.1948819	9.735040991	9.66E-07	1124.042404	1780.794178
Polish Time	-548.3254627	27.04266823	-20.27630773	4.61E-10	-607.8460043	-488.804921
Site 9 Init	0.510362247	0.100538607	5.07628126	0.000357	0.289078153	0.731646342

RESIDUAL OUTPUT

Observation	Predicted Site 9 Final	Residuals	Standard Residuals
1	1162.786714	25.01328601	0.857150304
2	1469.470519	20.3294812	0.696646614
3	1239.596232	-1.49623223	-0.051272588
4	1447.291421	-22.69142104	-0.777585098
5	977.6967345	50.60326553	1.734062627
6	1213.873975	-0.07397496	-0.002534959
7	1266.032997	-29.23299665	-1.001750508
8	1462.347107	12.55289266	0.430160026
9	1204.126056	-5.626056035	-0.192792568
10	964.0044866	-6.944486573	-0.237972283
11	1032.662749	-27.36274852	-0.937661218
12	1233.420849	40.77915096	1.397411825
13	1143.903311	-37.60331084	-1.288582768
14	1126.34685	-18.24684953	-0.625279406


Polish Time Residual Plot
Residuals
60
50
40
30
20
10
0
-10
-20
-30
-40
0
0.5
1
1.5
2
2.5
Polish Time


Site 9 Init Residual Plot
Residuals
60
50
40
30
20
10
0
-10
-20
-30
-40
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Site 9 Init

Data and Regression Results of Back End Experiment #1

Polish Time	Back Pressure	Site 1 Init	Site 2 Init	Site 3 Init	Site 4 Init	Site 5 Init	Site 6 Init	Site 7 Init	Site 8 Init	Site 9 Init
2.5	1.5	15106.0	15147.0	15201.0	15162.0	15102.0	15110.0	14984.0	14980.0	14929.0
2.5	1.5	15122.0	15259.0	15311.0	15291.0	15210.0	15263.0	15210.0	15050.0	15004.0
4.0	1.5	15158.0	15183.0	15236.0	15199.0	15138.0	15081.0	14963.0	14966.0	14920.0
2.5	1.5	15213.0	15298.0	15349.0	15343.0	15269.0	15254.0	15220.0	15056.0	15013.0
2.5	1.5	15218.0	15245.0	15299.0	15259.0	15197.0	15143.0	15026.0	15026.0	14982.0
2.5	1.5	15170.0	15273.0	15326.0	15310.0	15231.0	15227.0	15189.0	15019.0	14978.0
2.5	0.0	15195.0	15213.0	15271.0	15231.0	15167.0	15116.0	15005.0	14998.0	14959.0
2.5	3.0	15157.0	15242.0	15301.0	15284.0	15204.0	15182.0	15159.0	14985.0	14933.0
1.0	1.5	15293.0	15327.0	15380.0	15331.0	15270.0	15256.0	15126.0	15119.0	15084.0
2.5	1.5	15264.0	15365.0	15414.0	15394.0	15318.0	15324.0	15275.0	15098.0	15068.0
1.6	2.4	14717.0	14753.0	14810.0	14765.0	14706.0	14686.0	14572.0	14568.0	14523.0
3.4	0.6	14704.0	14741.0	14799.0	14757.0	14698.0	14678.0	14562.0	14559.0	14514.0
1.6	0.6	14665.0	14708.0	14755.0	14717.0	14659.0	14639.0	14521.0	14521.0	14481.0
3.4	2.4	14687.0	14730.0	14789.0	14741.0	14686.0	14670.0	14558.0	14552.0	14509.0
3.4	2.4	15738.0	15823.0	15875.0	15862.0	15783.0	15788.0	15734.0	15550.0	15516.0
1.6	2.4	15714.0	15797.0	15845.0	15832.0	15758.0	15761.0	15697.0	15529.0	15499.0
1.6	0.6	15684.0	15802.0	15853.0	15836.0	15757.0	15788.0	15742.0	15568.0	15526.0
3.4	0.6	15760.0	15856.0	15905.0	15898.0	15825.0	15825.0	15784.0	15613.0	15571.0
2.5	1.5	14389.0	14446.0	14497.0	14455.0	14395.0	14393.0	14272.0	14266.0	14230.0
2.5	1.5	16075.0	16170.0	16221.0	16208.0	16131.0	16115.0	16076.0	15903.0	15858.0

Polish Time	Back Pressure	Site 1 Final	Site 2 Final	Site 3 Final	Site 4 Final	Site 5 Final	Site 6 Final	Site 7 Final	Site 8 Final	Site 9 Final
2.5	1.5	12264.0	11989.0	12045.0	12187.0	12115.0	12343.0	12397.0	12265.0	12324.0
2.5	1.5	12043.0	12059.0	12122.0	11965.0	11908.0	12554.0	12203.0	12153.0	12064.0
4.0	1.5	10273.0	10138.0	9999.6	10208.0	9982.1	10489.0	10452.0	10272.0	10223.0
2.5	1.5	12120.0	12002.0	12090.0	11814.0	11900.0	12336.0	12032.0	12416.0	12114.0
2.5	1.5	12161.0	11988.0	12170.0	11912.0	11834.0	12310.0	12102.0	11831.0	12439.0
2.5	1.5	12191.0	12122.0	12255.0	11919.0	12069.0	12441.0	12223.0	12140.0	12251.0
2.5	0.0	12351.0	12104.0	12204.0	12205.0	12105.0	11999.0	11882.0	11610.0	12042.0
2.5	3.0	12150.0	12172.0	12136.0	11969.0	11973.0	12512.0	12473.0	12129.0	12398.0
1.0	1.5	14180.0	14114.0	14211.0	14018.0	14010.0	14183.0	13881.0	14021.0	14031.0
2.5	1.5	12257.0	12197.0	12169.0	12132.0	12073.0	12419.0	12273.0	12068.0	12219.0
1.6	2.4	12787.0	12732.0	12792.0	12601.0	12606.0	13065.0	12566.0	12790.0	12719.0
3.4	0.6	10681.0	10563.0	10736.0	10396.0	10282.0	10880.0	10360.0	10359.0	10916.0
1.6	0.6	12777.0	12729.0	12810.0	12538.0	12524.0	12776.0	12596.0	12360.0	12628.0
3.4	2.4	10715.0	10507.0	10707.0	10289.0	10415.0	11068.0	10532.0	10793.0	11049.0
3.4	2.4	11602.0	11530.0	11456.0	11374.0	11350.0	11882.0	12308.0	11721.0	11964.0
1.6	2.4	13794.0	13745.0	13867.0	13729.0	13635.0	14110.0	13808.0	13678.0	13738.0
1.6	0.6	13726.0	13716.0	13854.0	13816.0	13592.0	13914.0	13871.0	13375.0	13771.0
3.4	0.6	11699.0	11651.0	11614.0	11318.0	11562.0	12005.0	11659.0	11579.0	11830.0
2.5	1.5	11447.0	11286.0	11235.0	11346.0	11185.0	11529.0	11421.0	11300.0	11410.0
2.5	1.5	13012.0	12971.0	13054.0	12705.0	12837.0	13184.0	12925.0	13051.0	13116.0

Site 1 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.997335769
R Square	0.994678635
Adjusted R Square	0.938827448
Standard Error	76.1031866
Observations	20

ANOVA

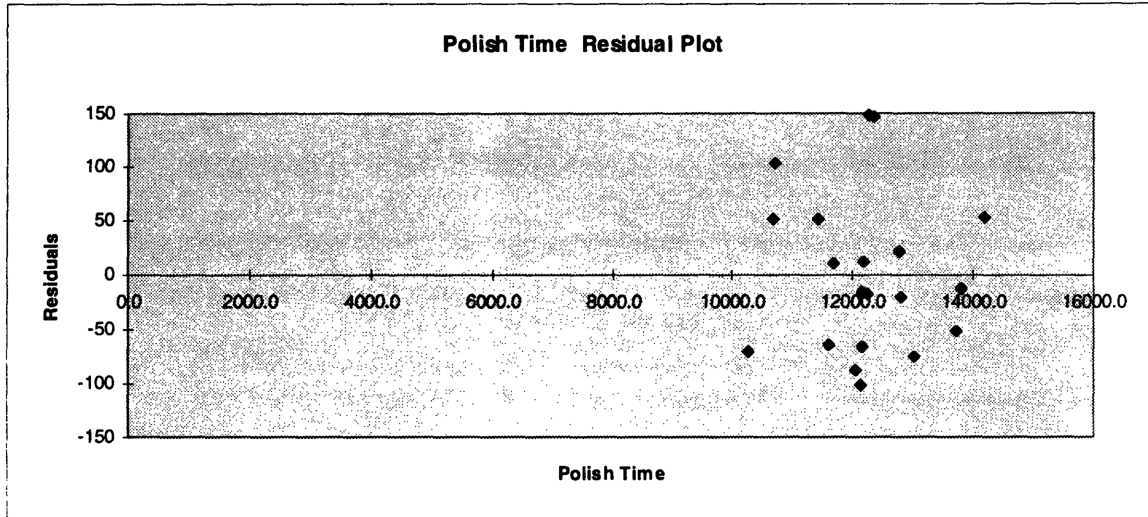
	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	19486684.49	9743342.245	1682.2955	2.89259E-20
Residual	18	104250.5102	5791.69501		
Total	20	19590935			

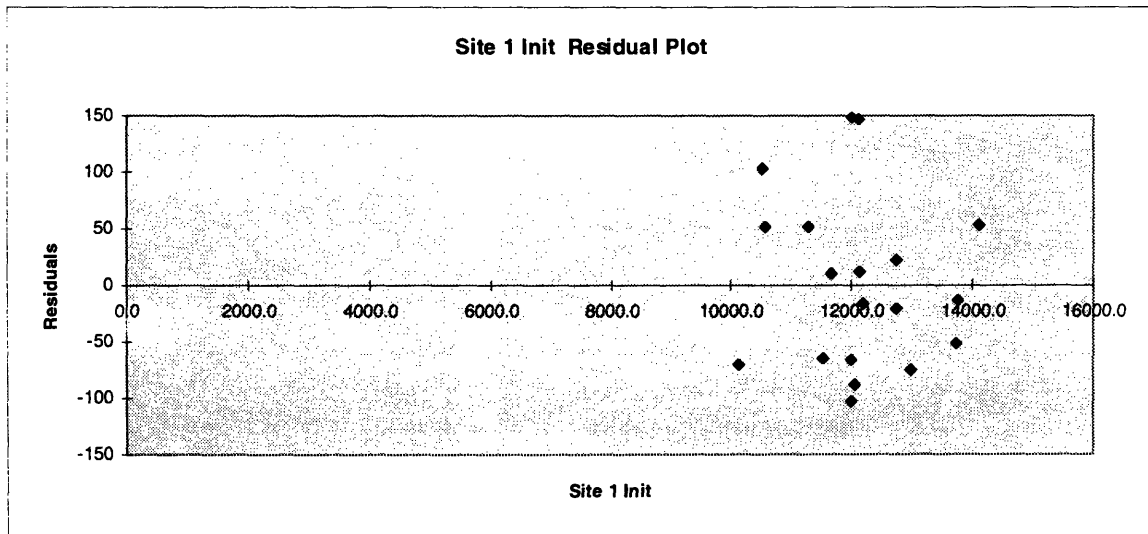
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Polish Time	-1216.013742	22.97901808	-52.91843791	3.289E-21	-1264.290905	-1167.736579
Site 1 Init	1.00324024	0.003937964	254.7611489	1.796E-33	0.994966878	1.011513602

RESIDUAL OUTPUT

Observation	*Predicted Site 1 Final*	*Residuals*	*Standard Residuals*
1	12114.91271	149.0872903	1.959015082
2	12130.96455	-87.96455353	-1.155859005
3	10343.06059	-70.06058952	-0.920599947
4	12222.25942	-102.2594154	-1.343694265
5	12227.27562	-66.27561656	-0.870865197
6	12179.12009	11.87991495	0.156102727
7	12204.20109	146.798909	1.928945627
8	12166.07796	-16.07796193	-0.211265292
9	14126.53925	53.46075279	0.702477192
10	12273.42467	-16.4246676	-0.215821023
11	12806.90449	-19.90448654	-0.261546033
12	10629.3579	51.64209692	0.678579955
13	12754.73599	22.26400593	0.292550246
14	10612.30282	102.697181	1.349446529
15	11666.70831	-64.70831114	-0.850270718

16	13807.13501	-13.13500574	-0.172594688
17	13777.0378	-51.03779854	-0.670639441
18	11688.7796	10.22040358	0.134296657
19	11395.58946	51.41054232	0.675537315
20	13087.0525	-75.05250217	-0.98619395





Site 2 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.998352934
R Square	0.996708582
Adjusted R Square	0.940970169
Standard Error	61.83799552
Observations	20

ANOVA

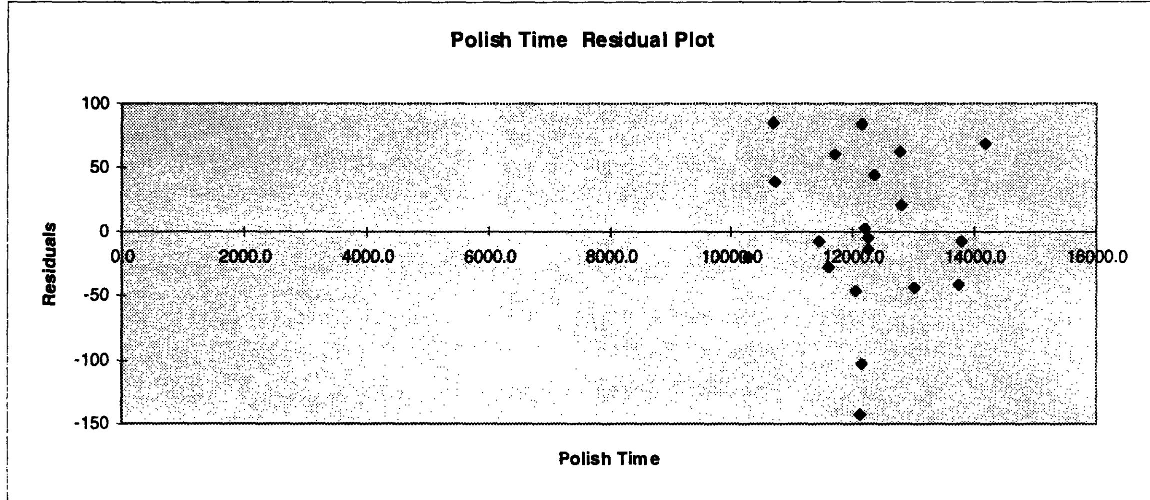
	df	SS	MS	F	Significance F
Regression	2	20843392.87	10421696.44	2725.3834	4.8689E-22
Residual	18	68830.87842	3823.93769		
Total	20	20912223.75			

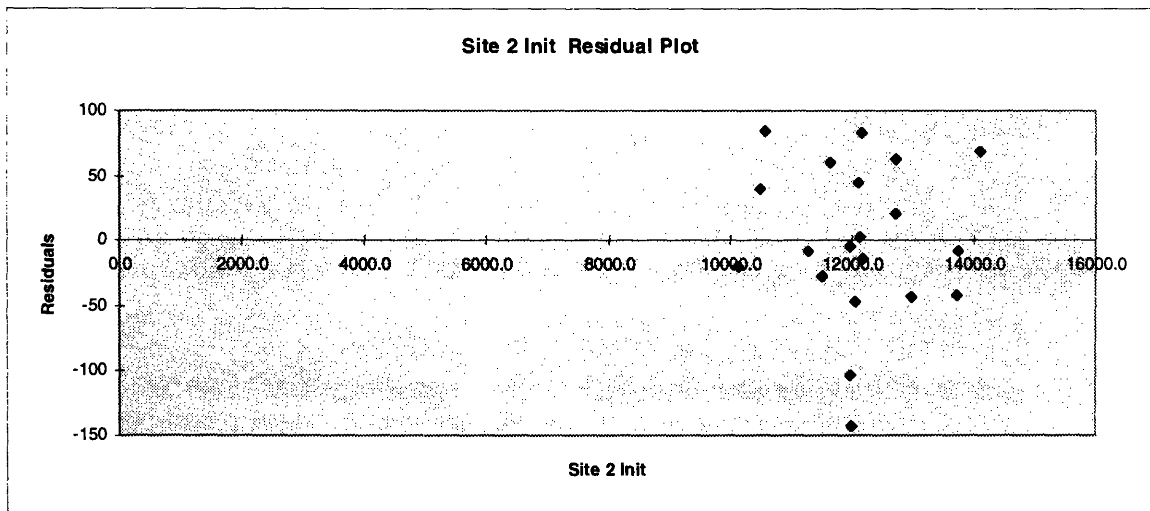
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Polish Time	-1247.669741	18.65710267	-66.87371359	4.968E-23	-1286.86689	-1208.47259
Site 2 Init	0.997742297	0.00318309	313.4508703	4.305E-35	0.991054868	1.004429726

RESIDUAL
OUTPUT

Observation	Predicted Site 2 Final	Residuals	Standard Residuals
1	11993.62823	-4.628226414	-0.07484438
2	12105.37536	-46.37536372	-0.749949337
3	10158.04234	-20.04233824	-0.324110412
4	12144.28731	-142.2873133	-2.300969042
5	12091.40697	-103.4069716	-1.67222386
6	12119.34376	2.65624412	0.042954887
7	12059.47922	44.52078196	0.719958362
8	12088.41374	83.58625534	1.351697361
9	14044.72645	69.27354918	1.120242475
10	12211.13605	-14.13604724	-0.228598083
11	12710.94383	21.05616962	0.340505371
12	10478.11878	84.88121543	1.372638533
13	12666.04543	62.954573	1.018056495
14	10467.14362	39.8563807	0.644528988

15	11557.67595	-27.6759503	-0.447555747
16	13752.58679	-7.586788813	-0.122688143
17	13757.5755	-41.5755003	-0.672329366
18	11590.60145	60.39855389	0.976722376
19	11294.21088	-8.210875975	-0.132780435
20	13014.3186	-43.3185966	-0.700517477





Site 3 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.995533174
R Square	0.9910863
Adjusted R Square	0.935035539
Standard Error	104.5969009
Observations	20

ANOVA

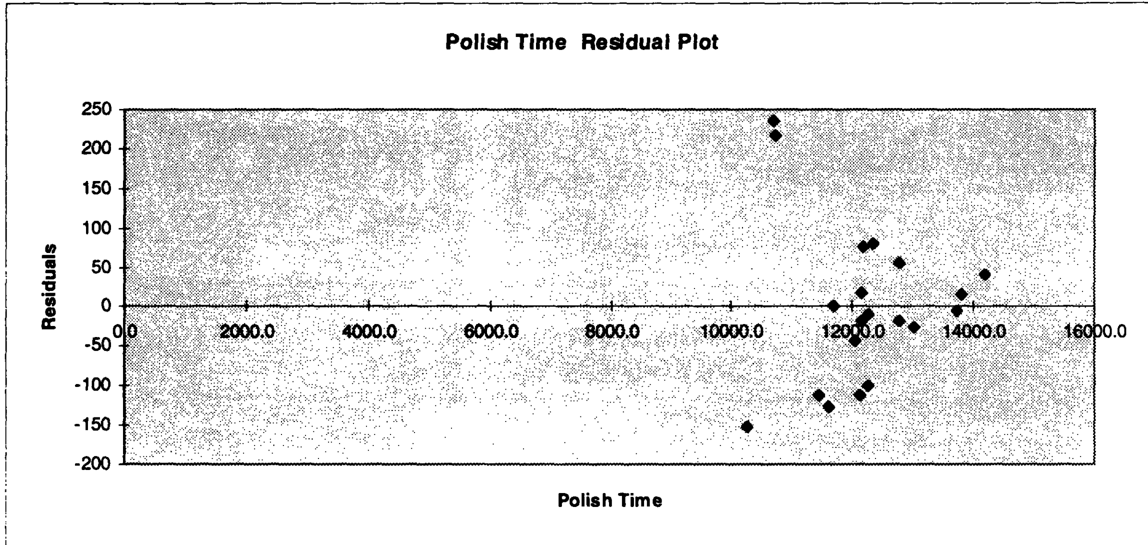
	df	SS	MS	F	Significance F
Regression	2	21895940.57	10947970.29	1000.682	2.32445E-18
Residual	18	196929.2103	10940.51168		
Total	20	22092869.78			

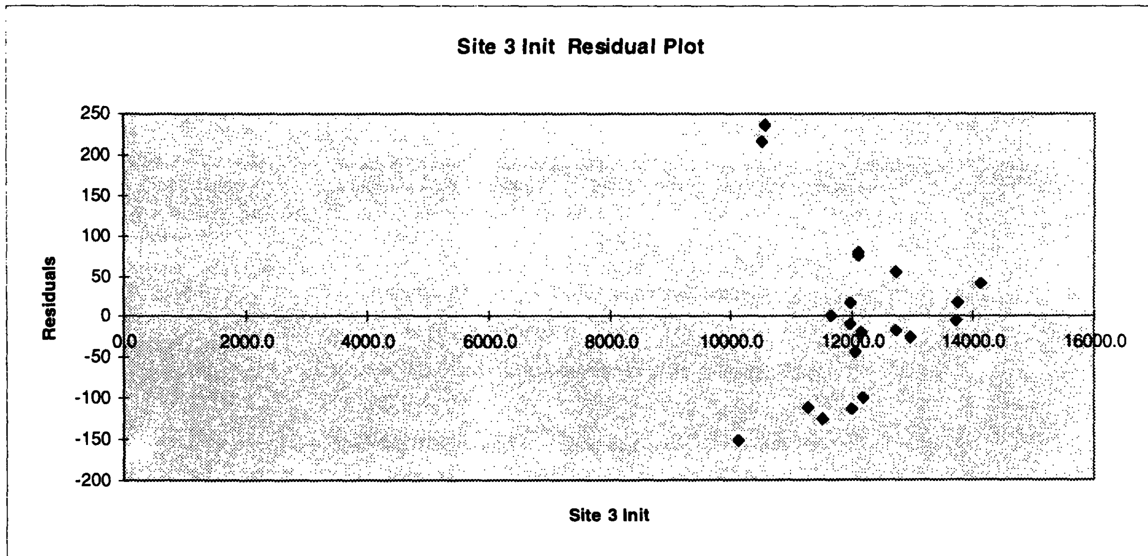
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Polish Time	-1291.28877	31.56630634	-40.90718616	3.26E-19	-1357.60717	-1224.97037
Site 3 Init	1.005343662	0.005366948	187.3212944	4.54E-31	0.994068114	1.01661921

RESIDUAL OUTPUT

Observation	Predicted Site 3 Final	Residuals	Standard Residuals
1	12054.00708	-9.00707862	-0.08611229
2	12164.59488	-42.59488142	-0.407228905
3	10152.26095	-152.6609519	-1.45951697
4	12202.79794	-112.7979406	-1.078406144
5	12152.53076	17.46924252	0.167014915
6	12179.67504	75.32496365	0.720145272
7	12124.38113	79.61886505	0.761197171
8	12154.54144	-18.5414448	-0.177265719
9	14170.89675	40.10325104	0.383407641
10	12268.14528	-99.14527859	-0.947879695
11	12810.16471	-18.16471207	-0.17366396
12	10500.61192	235.3880787	2.250430716
13	12754.87081	55.12918933	0.527063315
14	10490.55848	216.4415153	2.069291856
15	11582.3617	-126.3617015	-1.208082652

16	13850.6954	16.30459794	0.155880316
17	13858.73815	-4.738151354	-0.045299156
18	11612.52201	1.477988679	0.01413033
19	11346.24514	-111.2451407	-1.063560581
20	13079.45761	-25.45761368	-0.243387839





Site 4 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.990432031
R Square	0.980955607
Adjusted R Square	0.92434203
Standard Error	151.3107588
Observations	20

ANOVA

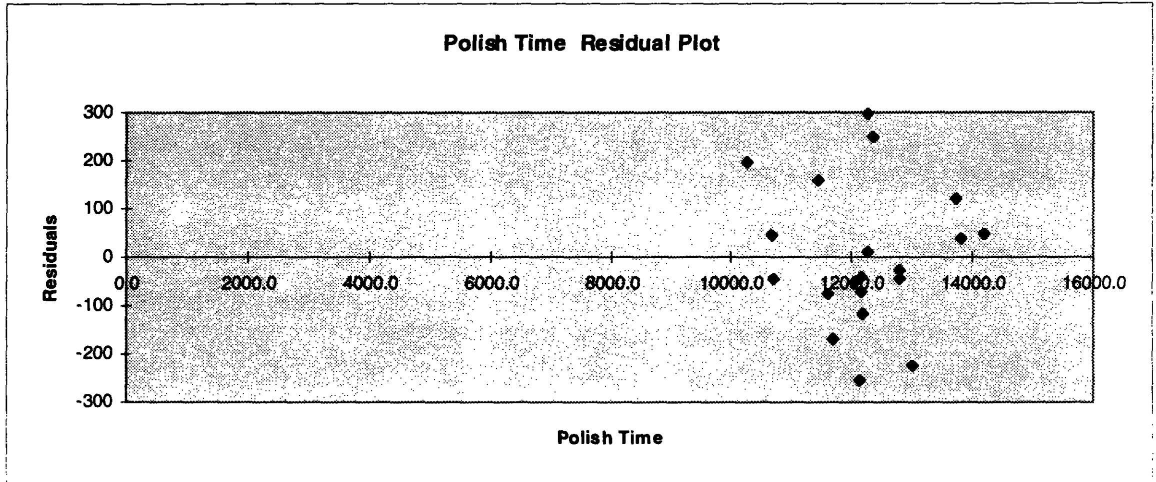
	df	SS	MS	F	Significance F
Regression	2	21227279.93	10613639.96	463.58	1.48227E-15
Residual	18	412109.0234	22894.94574		
Total	20	21639388.95			

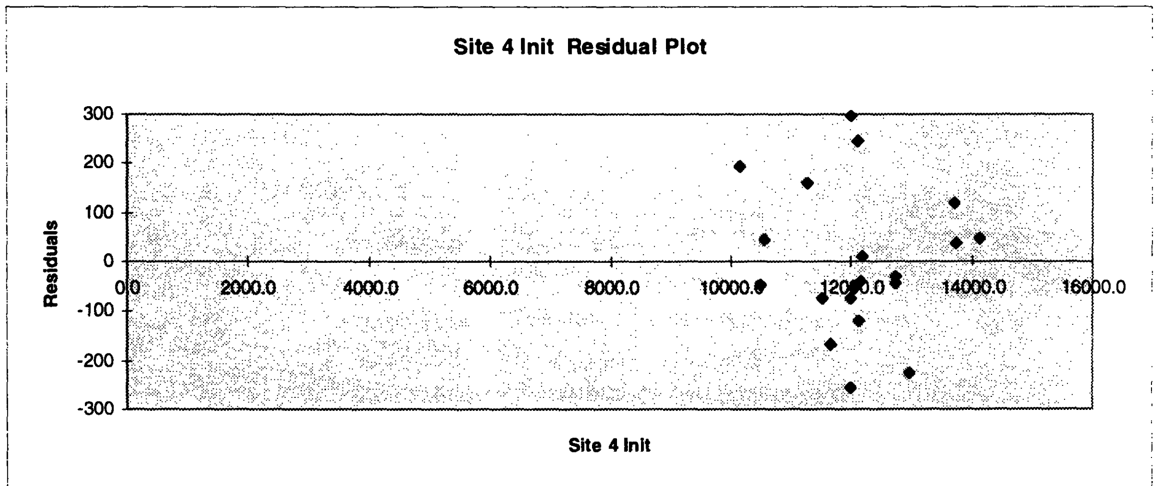
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Polish Time	-1275.781622	45.66647481	-27.93694121	2.8E-16	-1371.7234	-1179.839844
Site 4 Init	0.994528727	0.007778372	127.8582077	4.4E-28	0.97818696	1.010870493

RESIDUAL OUTPUT

Observation	Predicted Site 4 Final	Residuals	Standard Residuals
1	11889.5905	297.4095023	1.965554232
2	12017.8847	-52.88470339	-0.349510529
3	10012.71563	195.2843727	1.290617892
4	12069.6002	-255.6001972	-1.689240072
5	11986.05978	-74.05978414	-0.489454846
6	12036.78075	-117.7807492	-0.778403004
7	11958.21298	246.7870202	1.630994531
8	12010.923	-41.92300231	-0.277065574
9	13971.33829	46.66171432	0.308383321
10	12120.32116	11.67883776	0.07718445
11	12630.20824	-29.2082369	-0.193034766
12	10351.36072	44.63928034	0.295017226
13	12582.47086	-44.47085803	-0.293904137
14	10335.44826	-46.44826004	-0.30697262
15	11450.31496	-76.31496258	-0.504359129

16	13691.37039	37.62961179	0.24869092
17	13695.3485	120.6514969	0.797375532
18	11486.118	-168.1179967	-1.111077613
19	11186.45869	159.5413121	1.05439503
20	12929.86755	-224.8675457	-1.486130579





Site 5 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.995941699
R Square	0.991899867
Adjusted R Square	0.935894304
Standard Error	98.32899457
Observations	20

ANOVA

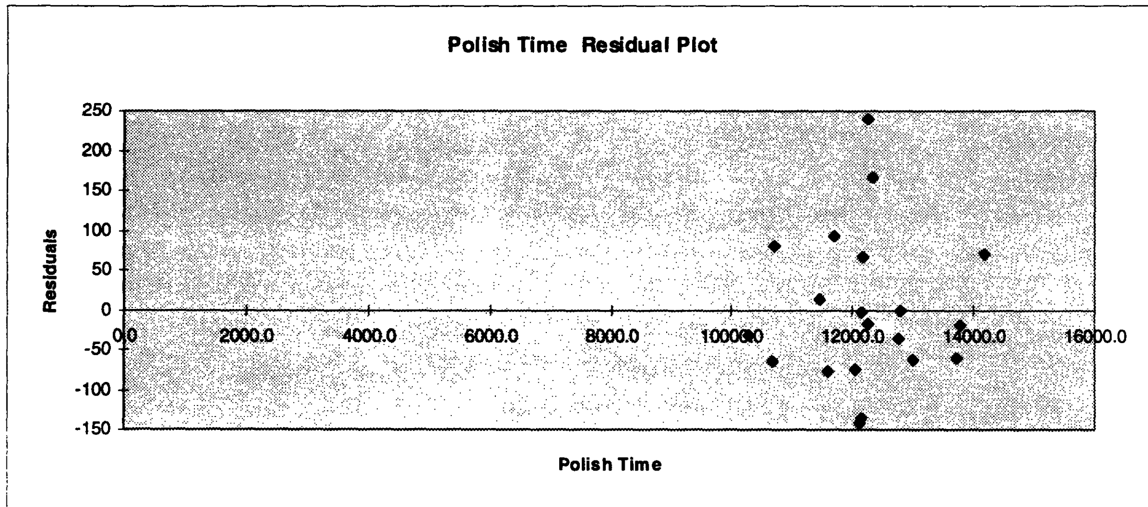
	df	SS	MS	F	Significance F
Regression	2	21311370.75	10655685.37	1102.0929	1.03002E-18
Residual	18	174034.6411	9668.591172		
Total	20	21485405.39			

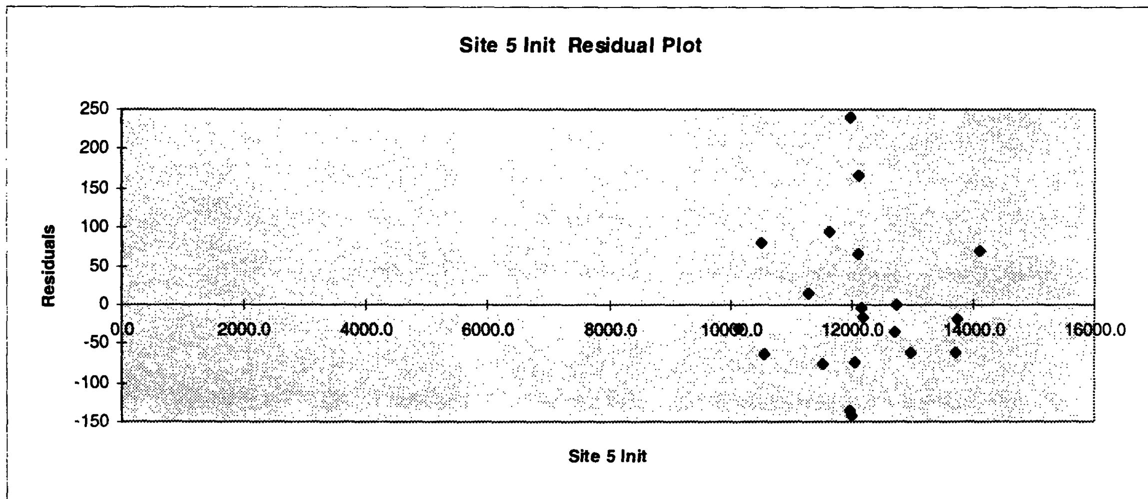
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Polish Time	-1265.093823	29.68055452	-42.6236586	1.568E-19	-1327.450402	-1202.737243
Site 5 Init	0.995729943	0.005078295	196.0756213	1.997E-31	0.985060832	1.006399055

RESIDUAL
OUTPUT

Observation	Predicted Site 5 Final	Residuals	Standard Residuals
1	11874.77905	240.2209509	2.443032718
2	11982.31788	-74.31788301	-0.75580843
3	10012.98459	-30.88459281	-0.314094464
4	12041.06595	-141.0659497	-1.43463228
5	11969.37339	-135.3733937	-1.376739326
6	12003.22821	65.77178818	0.668895156
7	11939.5015	165.4985046	1.683109904
8	11976.3435	-3.343503348	-0.034003229
9	13939.70241	70.29758612	0.714922251
10	12089.85672	-16.8567169	-0.171431804
11	12606.40349	-0.403493834	-0.004103508
12	10346.57065	-64.57064962	-0.656679649
13	12559.60419	-35.60418649	-0.362092449
14	10334.62189	80.3781097	0.817440573

15	11426.93764	-76.93763828	-0.782451185
16	13653.91139	-18.91139436	-0.192327751
17	13652.91566	-60.91566442	-0.619508668
18	11468.7583	93.24170409	0.94826256
19	11170.79798	14.20202092	0.144433704
20	12899.38516	-62.38516094	-0.63445336





Site 6 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.995828282
R Square	0.991673968
Adjusted R Square	0.931870905
Standard Error	95.77167584
Observations	20

ANOVA

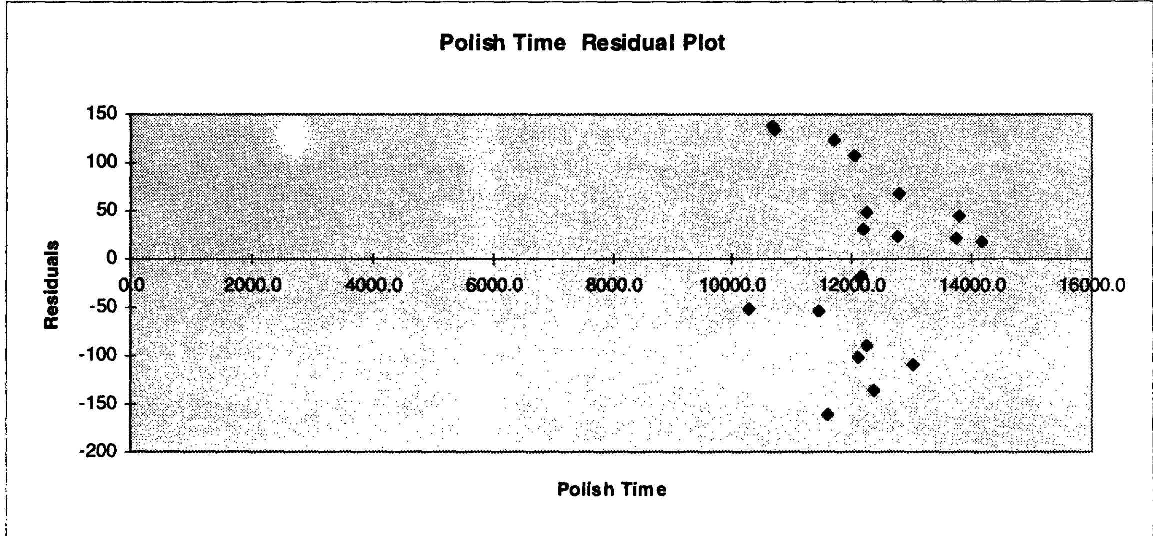
	df	SS	MS	F	Significance F
Regression	3	18571797.31	6190599.105	674.9296	4.74902E-17
Residual	17	155927.6362	9172.213894		
Total	20	18727724.95			

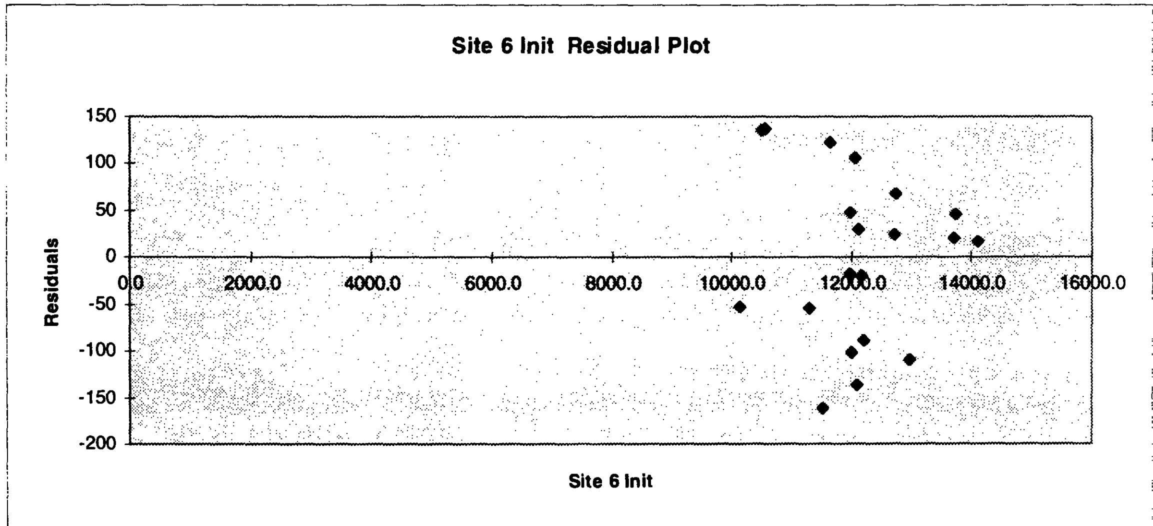
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Polish Time	-1150.478482	28.86714544	-39.85425176	3.12E-18	-1211.38292	-1089.574044
Site 6 Init	0.99310661	0.005686977	174.6281986	4.18E-29	0.98110812	1.0051051
Back Pressure	110.2338499	28.87098883	3.818152905	0.001376	49.32130281	171.1463969

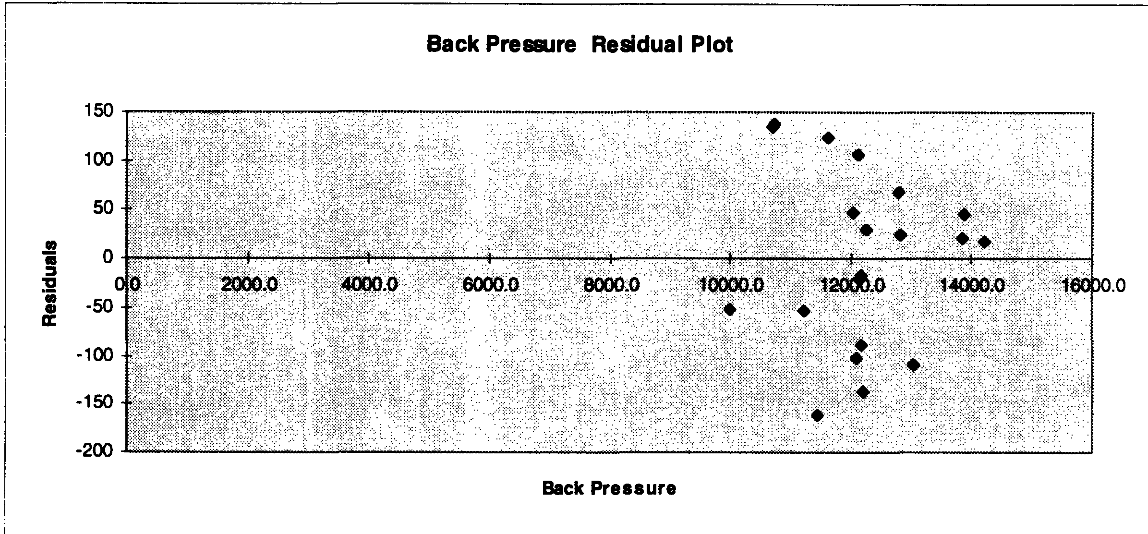
RESIDUAL
OUTPUT

Observation	Predicted Site 6 Final	Residuals	Standard Residuals
1	12294.99545	48.00454965	0.501239529
2	12446.94076	107.0592383	1.117859089
3	10540.47764	-51.47763557	-0.537503757
4	12438.0028	-102.0028022	-1.065062309
5	12327.76797	-17.76796849	-0.185524252
6	12411.18892	29.81107625	0.311272367
7	12135.60332	-136.6033152	-1.426343582
8	12531.8499	-19.84990108	-0.207262752
9	14165.70674	17.29326148	0.180567598
10	12507.52026	-88.52026494	-0.92428439
11	12997.05456	67.94543849	0.709452329
12	10742.83708	137.1629192	1.432186687
13	12751.95762	24.04237893	0.251038511
14	10933.31316	134.6868423	1.40633273
15	12043.60635	-161.6063479	-1.687412761

16	14064.64417	45.35583248	0.473582947
17	13893.03712	20.96288376	0.218883961
18	11881.93036	123.0696372	1.285031677
19	11582.93801	-53.93801081	-0.563193766
20	13293.06759	-109.0675936	-1.138829332






Back Pressure Residual Plot
150
100
50
0
-50
-100
-150
-200
Residuals
0.0
2000.0
4000.0
6000.0
8000.0
10000.0
12000.0
14000.0
16000.0
Back Pressure

Site 7 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.984838436
R Square	0.969906746
Adjusted R Square	0.907542834
Standard Error	185.3756736
Observations	20

ANOVA

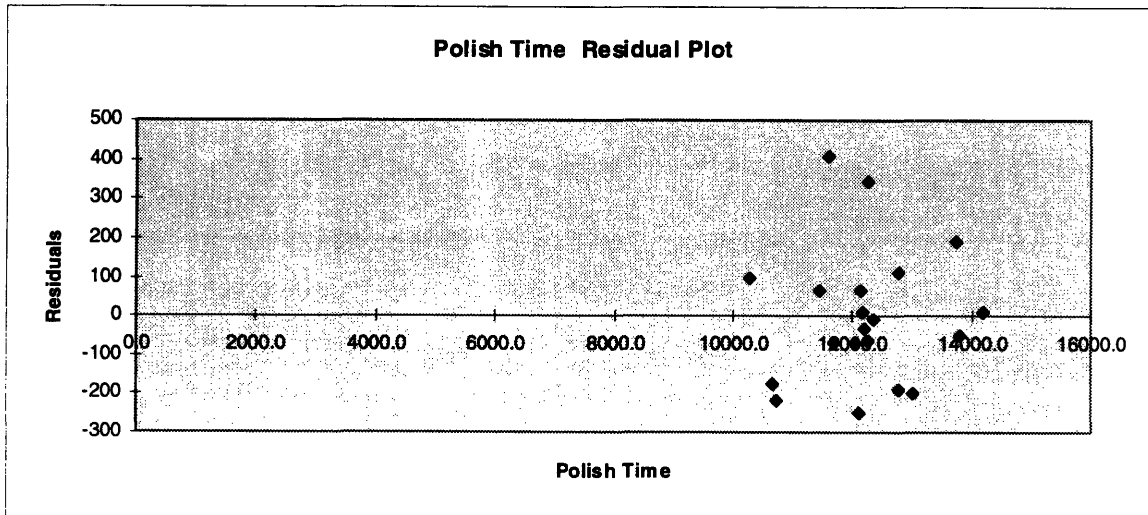
	df	SS	MS	F	Significance F
Regression	3	18828478.81	6276159.605	182.6369	1.38445E-12
Residual	17	584190.386	34364.14035		
Total	20	19412669.2			

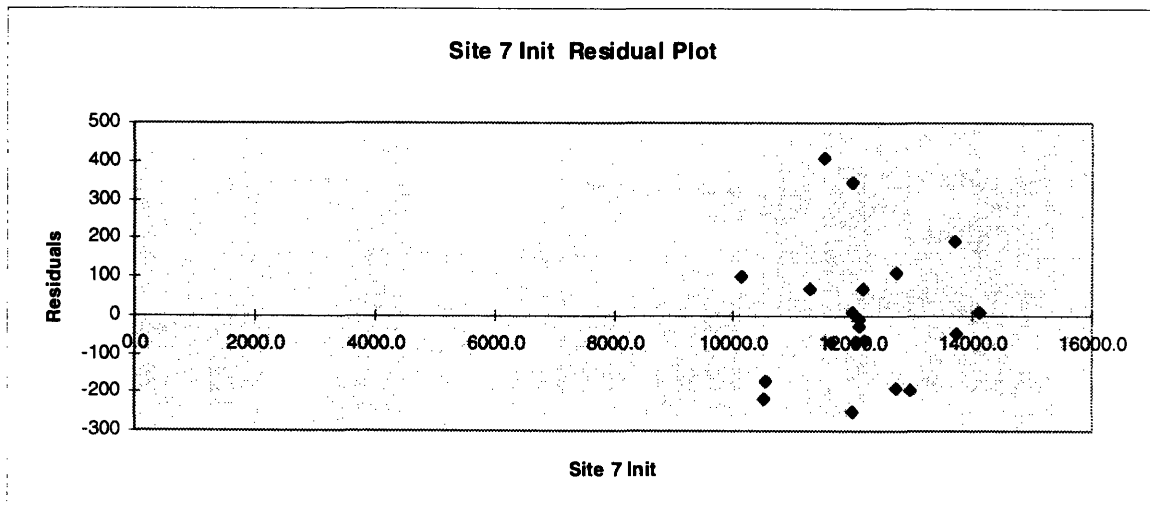
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Polish Time	-1119.711645	55.86609285	-20.04277708	2.89E-13	-1237.578963	-1001.844327
Site 7 Init	0.978964751	0.011072793	88.41172324	4.37E-24	0.955603166	1.002326335
Back Pressure	121.8290454	55.92513516	2.178430953	0.043739	3.83715932	239.8209316

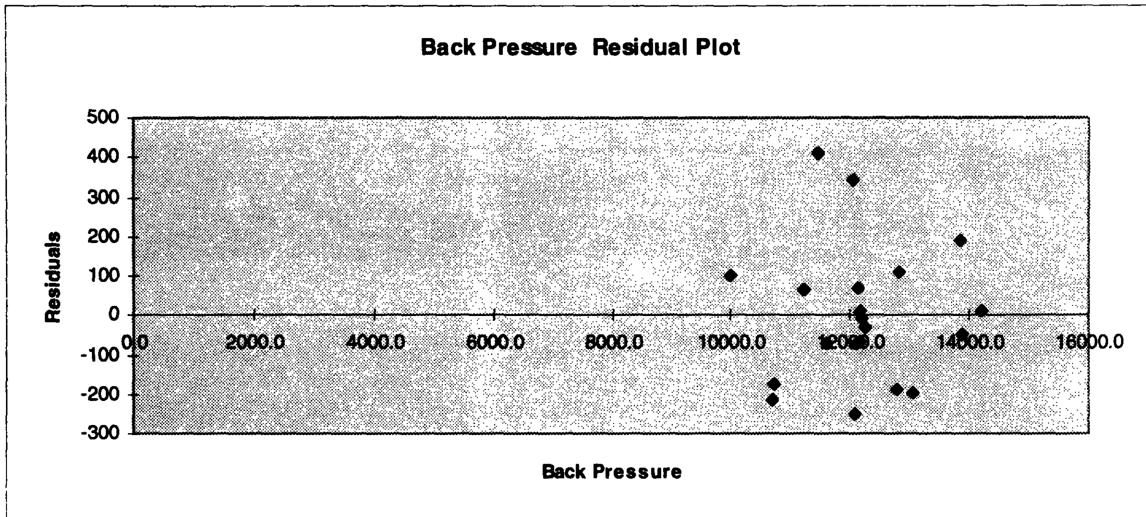
RESIDUAL OUTPUT

Observation	Predicted Site 7 Final	Residuals	Standard Residuals
1	12052.27228	344.7277214	1.859616824
2	12273.51831	-70.51831226	-0.380407585
3	10352.14655	99.85344862	0.538654542
4	12283.30796	-251.3079598	-1.355668492
5	12093.3888	8.61120185	0.046452707
6	12252.96005	-29.9600525	-0.161618037
7	11890.08697	-8.086970213	-0.043624765
8	12406.33468	66.66532185	0.359622817
9	13870.85274	10.14725931	0.054738894
10	12337.15102	-64.15102105	-0.346059544
11	12755.12831	-189.1283063	-1.020243394
12	10532.95965	-172.9596489	-0.933022363
13	12485.90882	110.0911778	0.593881471
14	10748.33607	-216.3360717	-1.167014353
15	11899.59862	408.4013816	2.203101268
16	13856.46365	-48.46365074	-0.261434792

17	13681.22478	189.7752173	1.023733123
18	11729.25457	-70.25457416	-0.378984862
19	11355.24938	65.7506238	0.354688523
20	13121.30179	-196.3017863	-1.05894038






Back Pressure Residual Plot
500
400
300
200
100
0
-100
-200
-300
Residuals
0.0
2000.0
4000.0
6000.0
8000.0
10000.0
12000.0
14000.0
16000.0
Back Pressure

Site 8 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.99041864
R Square	0.980929082
Adjusted R Square	0.919861915
Standard Error	145.3615472
Observations	20

ANOVA

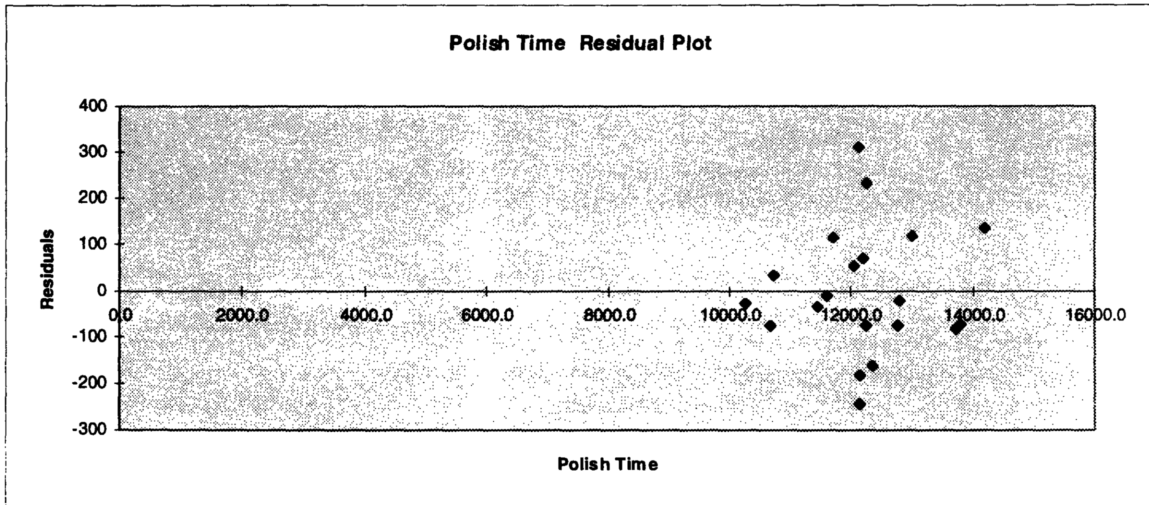
	df	SS	MS	F	Significance F
Regression	3	18476257.3	6158752.433	291.46987	3.59991E-14
Residual	17	359209.6497	21129.9794		
Total	20	18835466.95			

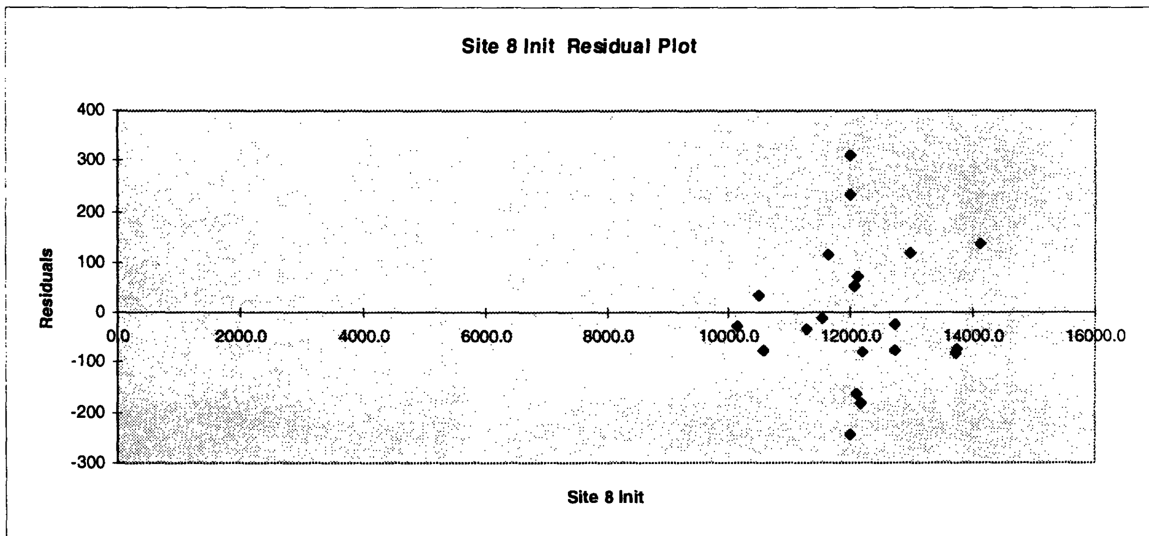
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Polish Time	-1144.93082	43.86581435	-26.10075379	3.714E-15	-1237.479728	-1052.38191
Site 8 Init	0.975915098	0.008729414	111.7961793	8.15E-26	0.95749762	0.994332577
Back Pressure	183.0842727	43.77154776	4.182723299	0.0006245	90.73425036	275.434295

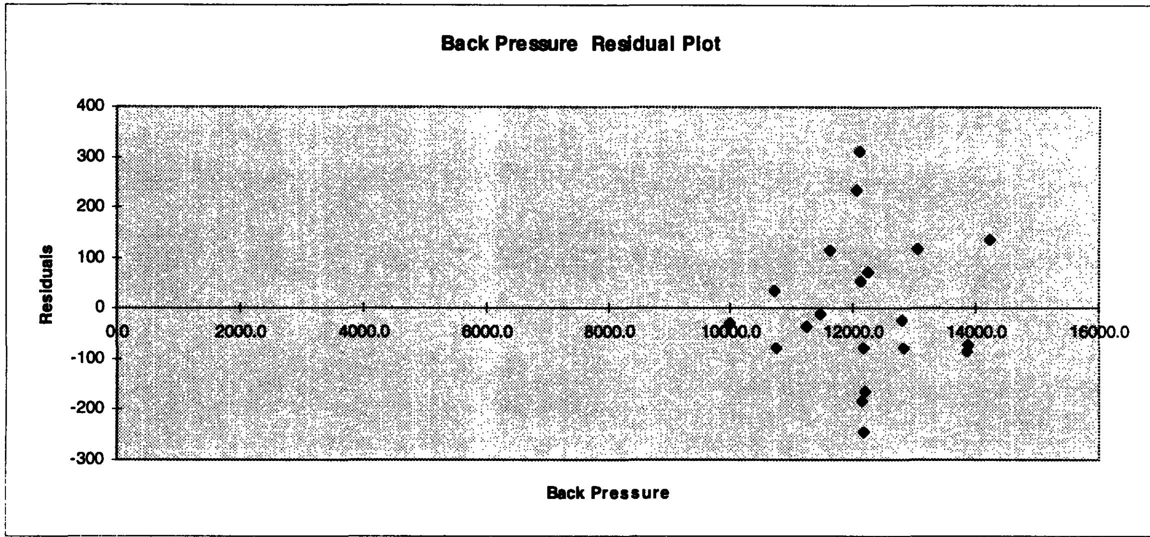
RESIDUAL OUTPUT

Observation	Predicted Site 8 Final	Residuals	Standard Residuals
1	12031.50753	233.4924679	1.606287718
2	12099.82159	53.17841104	0.365835478
3	10300.44849	-28.44849068	-0.195708502
4	12105.67708	310.3229204	2.134835013
5	12076.39963	-245.3996266	-1.688201807
6	12069.56822	70.43177909	0.484528271
7	11774.44759	-164.4475948	-1.131300526
8	12311.01352	-182.0135166	-1.252143501
9	13884.55596	136.4440392	0.93865291
10	12146.66551	-78.66551368	-0.541171412
11	12813.19479	-23.19478678	-0.15956618
12	10436.883	-77.88300046	-0.535788191
13	12437.77509	-77.77508635	-0.535045807
14	10759.60329	33.39671442	0.229749305

15	11733.56655	-12.56655372	-0.08645033
16	13751.0492	-73.04919629	-0.502534527
17	13459.55819	-84.55819431	-0.58170951
18	11465.49751	113.5024859	0.780828824
19	11334.70415	-34.70415186	-0.238743688
20	12932.27717	118.7228322	0.816741666







Back Pressure Residual Plot
400
300
200
100
0
-100
-200
-300
Residuals
0.0
2000.0
4000.0
6000.0
8000.0
10000.0
12000.0
14000.0
16000.0
Back Pressure

Site 9 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.987477638
R Square	0.975112085
Adjusted R Square	0.918173867
Standard Error	154.5010787
Observations	20

ANOVA

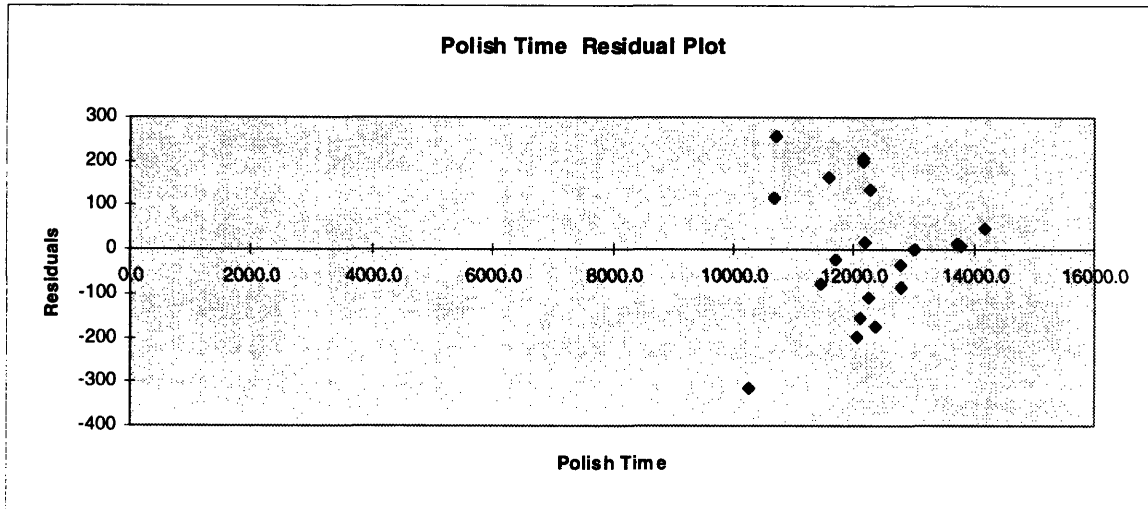
	df	SS	MS	F	Significance F
Regression	2	16834551.7	8417275.85	352.62129	1.44547E-14
Residual	18	429670.5	23870.58333		
Total	20	17264222.2			

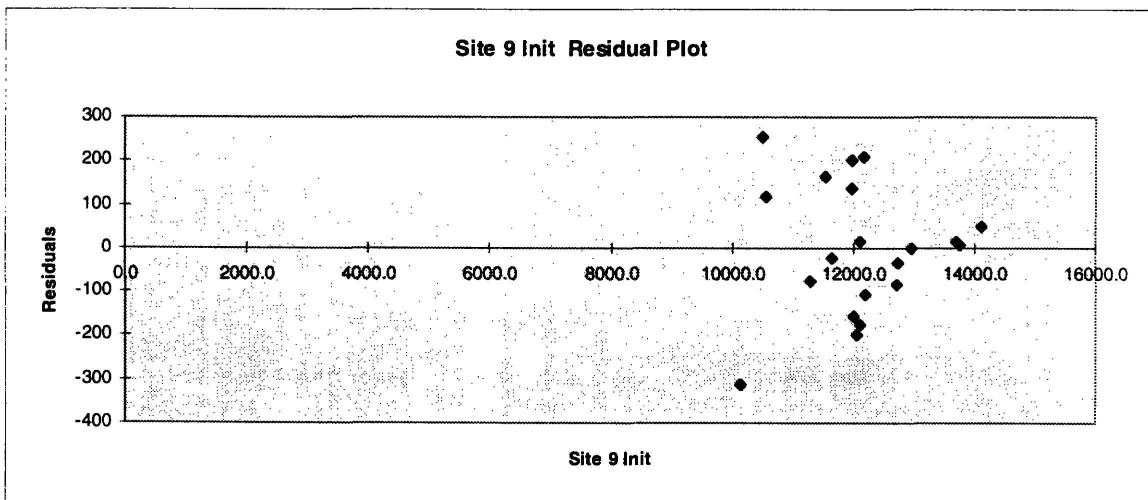
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Polish Time	-1094.208051	46.60411267	-23.47878735	5.946E-15	-1192.119734	-996.2963677
Site 9 Init	0.999535776	0.008091331	123.5316926	8.116E-28	0.982536508	1.016535044

RESIDUAL OUTPUT

Observation	Predicted Site 9 Final	Residuals	Standard Residuals
1	12186.54947	137.4505271	0.889641213
2	12261.51466	-197.5146561	-1.278403087
3	10536.24157	-313.2415744	-2.0274394
4	12270.51048	-156.510478	-1.01300573
5	12239.52487	199.475131	1.291092157
6	12235.52673	15.47327412	0.100149942
7	12216.53555	-174.5355461	-1.129672023
8	12190.54762	207.452384	1.342724502
9	13982.78959	48.21040544	0.31203928
10	12325.48495	-106.4849457	-0.689218137
11	12754.58311	-35.58311314	-0.230309804
12	10797.89696	118.1030395	0.764415631

13	12712.60261	-84.60261054	-0.547585889
14	10792.89928	256.1007184	1.657598254
15	11799.43181	164.568192	1.065158854
16	13730.13003	7.869969466	0.050937958
17	13757.1175	13.88250351	0.089853764
18	11854.40628	-24.40627572	-0.157968319
19	11487.87397	-77.87396542	-0.504035092
20	13115.11821	0.88179122	0.005707347





Data and Regression Results of Back End Experiment #2

Polish Time	Back Pressure	Site 1 Init	Site 2 Init	Site 3 Init	Site 4 Init	Site 5 Init	Site 6 Init	Site 7 Init	Site 8 Init	Site 9 Init
1.0	1.5	15305.0	15169.0	15276.0	15316.0	15206.0	15148.0	15215.0	15234.0	15086.0
2.5	1.5	15448.0	15363.0	15414.0	15342.0	15237.0	15387.0	15293.0	15158.0	15177.0
2.5	1.5	15307.0	15162.0	15270.0	15311.0	15205.0	15124.0	15199.0	15223.0	15080.0
3.4	0.6	15457.0	15389.0	15445.0	15364.0	15264.0	15412.0	15335.0	15197.0	15212.0
4.0	1.5	15340.0	15192.0	15289.0	15344.0	15244.0	15168.0	15238.0	15258.0	15104.0
2.5	0.0	15437.0	15366.0	15417.0	15335.0	15241.0	15386.0	15299.0	15169.0	15188.0
2.5	1.5	15367.0	15233.0	15338.0	15373.0	15271.0	15205.0	15276.0	15297.0	15150.0
1.6	2.4	15423.0	15355.0	15417.0	15320.0	15228.0	15410.0	15293.0	15157.0	15175.0
2.5	1.5	15346.0	15206.0	15318.0	15355.0	15245.0	15188.0	15254.0	15271.0	15131.0
3.4	2.4	15453.0	15383.0	15447.0	15352.0	15259.0	15431.0	15334.0	15184.0	15228.0
2.5	1.5	15559.0	15509.0	15561.0	15480.0	15381.0	15566.0	15469.0	15343.0	15363.0
2.5	3.0	15501.0	15422.0	15475.0	15391.0	15295.0	15448.0	15354.0	15216.0	15239.0
1.6	0.6	15436.0	15310.0	15405.0	15455.0	15361.0	15330.0	15395.0	15405.0	15256.0
2.5	1.5	15428.0	15299.0	15410.0	15444.0	15336.0	15300.0	15365.0	15376.0	15238.0
		Site 1 Final	**Site 2 Final**	**Site 3 Final**	**Site 4 Final**	**Site 5 Final**	**Site 6 Final**	**Site 7 Final**	**Site 8 Final**	**Site 9 Final**
		14175.0	13979.0	14102.0	13984.0	13903.0	14034.0	14022.0	14053.0	13887.0
		12516.0	12231.0	12214.0	12071.0	12026.0	12574.0	12333.0	11995.0	12029.0
		12363.0	12115.0	12193.0	12001.0	11939.0	12348.0	12081.0	12166.0	12169.0
		11529.0	11074.0	11101.0	10877.0	10929.0	11179.0	10972.0	10800.0	11084.0
		10757.0	10284.0	10255.0	10177.0	10384.0	10640.0	10428.0	10386.0	10573.0
		12683.0	12502.0	12552.0	12331.0	12117.0	12069.0	11869.0	11848.0	11930.0
		12517.0	12280.0	12373.0	12286.0	12204.0	12556.0	12423.0	12361.0	12610.0
		13457.0	13284.0	13206.0	13197.0	13081.0	13666.0	13237.0	13183.0	13279.0
		12396.0	12107.0	12076.0	12028.0	11992.0	12410.0	12046.0	12240.0	12054.0
		11371.0	11250.0	11014.0	10898.0	10894.0	11743.0	11240.0	11333.0	11257.0
		12499.0	12464.0	12424.0	12286.0	12127.0	12569.0	12406.0	12270.0	12416.0
		12391.0	12263.0	12201.0	12309.0	12130.0	12811.0	12432.0	12585.0	12542.0
		13508.0	13297.0	13372.0	13443.0	13392.0	13522.0	13332.0	13423.0	13457.0
		12425.0	12154.0	12319.0	12168.0	12178.0	12525.0	12399.0	12235.0	12645.0

Site 1 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.997137714
R Square	0.99428362
Adjusted R Square	0.902335188
Standard Error	72.31137044
Observations	14

ANOVA

	df	SS	MS	F	Significance F
Regression	3	10004493.22	3334831.074	637.764961	1.02641E-11
Residual	11	57518.27724	5228.934295		
Total	14	10062011.5			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Time	-1152.28015	26.1640273	-44.04062635	1.0097E-13	-1209.866815	-1094.693485
Site 1 Init	1.004699578	0.005104521	196.8254271	7.3034E-21	0.993464597	1.01593456
Pressure	-90.8199345	26.01718417	-3.490767252	0.00505173	-148.0833997	-33.55646926

RESIDUAL
OUTPUT

Observation	Predicted Site 1 Final	Residuals	Standard Residuals
1	14088.41699	86.58300528	1.197363634
2	12503.66881	12.33119081	0.170529071
3	12362.00617	0.99383136	0.013743777
4	11568.91971	-39.9197128	-0.552053053
5	10666.74103	90.25897051	1.248198865
6	12628.84702	54.15298443	0.748886159
7	12422.28814	94.71185666	1.309778201
8	13422.34271	34.65728768	0.479278535
9	12401.18945	-5.189452196	-0.071765369
10	11401.42503	-30.42503239	-0.420750322
11	12615.19046	-116.1904624	-1.606807639
12	12420.68799	-29.68798509	-0.410557633
13	13598.87969	-90.87968893	-1.256782832
14	12483.57482	-58.57481762	-0.81003606

Site 2 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.995219611
R Square	0.990462073
Adjusted R Square	0.906333913
Standard Error	95.84775572
Observations	14

ANOVA

	df	SS	MS	F	Significance F
Regression	2	11447983.92	5723991.961	623.06753	4.79799E-12
Residual	12	110241.5073	9186.792277		
Total	14	11558225.43			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Time	-1233.24547	34.69949542	-35.54073208	1.573E-13	-1308.849175	-1157.64177
Site 2 Init	1.0004105	0.005908596	169.314409	1.211E-21	0.987536775	1.013284225

RESIDUAL
OUTPUT

Observation	Predicted Site 2 Final	Residuals	Standard Residuals
1	13941.98141	37.01859426	0.386222859
2	12286.19284	-55.19283755	-0.575838601
3	12085.11033	29.88967297	0.311845309
4	11214.61504	-140.6150421	-1.467066611
5	10265.25444	18.74556318	0.195576443
6	12289.19407	212.805931	2.220249492
7	12156.13947	123.8605275	1.292263199
8	13375.77802	-91.77802197	-0.957539603
9	12129.12839	-22.12838903	-0.230870184
10	11208.61258	41.38742087	0.431803755
11	12432.25277	31.74722944	0.33122559
12	12345.21706	-82.21705705	-0.857788025
13	13330.75955	-33.75954947	-0.352220552
14	12222.16657	-68.16656554	-0.711196262

Site 3 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.994988502
R Square	0.990002119
Adjusted R Square	0.897275231
Standard Error	107.0508826
Observations	14

ANOVA

	df	SS	MS	F	Significance F
Regression	3	12482493	4160831.065	363.0777	1.6803E-10
Residual	11	126058.81	11459.89146		
Total	14	12608552			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Time	-1280.6728	38.719121	-33.07597803	2.3E-12	-1365.89305	-1195.452545
Site 3 Init	1.01417343	0.0075671	134.0245965	5E-19	0.99751841	1.030828446
Pressure	-110.1189689	38.525013	-2.858375876	0.015562	-194.911995	-25.32594326

RESIDUAL OUTPUT

Observation	Pred. Site 3 Final	Residuals	Standard Residuals
1	14046.66207	55.337933	0.516931119
2	12265.6088	-51.608801	-0.482095993
3	12119.56783	73.432172	0.685955788
4	11256.35646	-155.35646	-1.451239397
5	10217.82792	37.172077	0.347237461
6	12433.82978	118.17022	1.103869693
7	12188.53162	184.46838	1.723184104
8	13309.34304	-103.34304	-0.96536375
9	12168.24815	-92.248152	-0.861722482
10	11060.17066	-46.170661	-0.431296407
11	12414.6923	9.3077043	0.086946544
12	12162.29493	38.705073	0.361557716
13	13495.3871	-123.3871	-1.152602401
14	12261.55211	57.447892	0.536640996

Site 4 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.994867134
R Square	0.989760615
Adjusted R Square	0.905573999
Standard Error	106.7337936
Observations	14

ANOVA

	df	SS	MS	F	Significance F
Regression	2	13214216	6607108.241	579.9727	7.091E-12
Residual	12	136705.23	11392.1027		
Total	14	13350922			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Time	-1308.263551	38.532284	-33.95240043	2.71E-13	-1392.21819	-1224.308917
Site 4 Init	1.003086766	0.0065362	153.465846	3.94E-21	0.98884556	1.017327969

RESIDUAL
OUTPUT

Observation	Predicted Site 4 Final	Residuals	Standard Residuals
1	14055.01336	-71.013362	-0.665331565
2	12118.69829	-47.698291	-0.446890245
3	12087.6026	-86.602601	-0.811388769
4	10976.41164	-99.41164	-0.931397978
5	10158.30914	18.690862	0.175116627
6	12111.67668	219.32332	2.054862932
7	12149.79398	136.20602	1.276128341
8	13260.98494	-63.984943	-0.599481576
9	12131.73842	-103.73842	-0.971936025
10	10964.3746	-66.374598	-0.621870507
11	12257.12426	28.875735	0.270539761
12	12167.84954	141.15046	1.322453296
13	13396.40166	46.598344	0.436584723
14	12221.01314	-53.013141	-0.496685628

Site 5 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.996018006
R Square	0.992051868
Adjusted R Square	0.908056191
Standard Error	88.08301351
Observations	14

ANOVA

	df	SS	MS	F	Significance F
Regression	2	11620770	5810385.011	748.8944	1.7587E-12
Residual	12	93103.407	7758.617269		
Total	14	11713873			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Time	-1227.994191	31.804898	-38.61022212	5.87E-14	-1297.29111	-1158.697271
Site 5 Init	0.99299906	0.0054306	182.8520667	4.81E-22	0.98116677	1.004831352

RESIDUAL
OUTPUT

Observation	Predicted Site 5 Final	Residuals	Standard Residuals
1	13871.54952	31.450484	0.357055037
2	12060.3412	-34.341201	-0.389873141
3	12028.56523	-89.565231	-1.016827509
4	10994.23735	-65.237346	-0.740634811
5	10225.30091	158.69909	1.801699161
6	12064.3132	52.686803	0.598149411
7	12094.10317	109.89683	1.24765067
8	13144.31904	-63.319039	-0.718856415
9	12068.28519	-76.285194	-0.866060215
10	10989.27235	-95.272351	-1.081620019
11	12203.33307	-76.333066	-0.866603704
12	12117.93515	12.064853	0.136971397
13	13276.38791	115.61209	1.31253554
14	12158.64811	19.351892	0.219700611

Site 6 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.991213444
R Square	0.982504092
Adjusted R Square	0.888413926
Standard Error	131.3890551
Observations	14

ANOVA

	df	SS	MS	F	Significance F
Regression	3	10663725	3554574.978	205.9061	2.7591E-09
Residual	11	189893.92	17263.08379		
Total	14	10853619			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Time	-1171.8553	47.551038	-24.64415814	5.63E-11	-1276.51448	-1067.196118
Site 6 Init	0.985328018	0.0093443	105.446684	6.97E-18	0.96476129	1.005894748
Pressure	204.5986531	47.329604	4.322847348	0.001209	100.426844	308.7704618

RESIDUAL OUTPUT

Observation	Pred. Site 6 Final	Residuals	Standard Residuals
1	14060.7915	-26.791501	-0.203909685
2	12538.50195	35.498052	0.270175111
3	12279.36068	68.639321	0.522412778
4	11336.04514	-157.04514	-1.195268078
5	10564.93216	75.067838	0.571340118
6	12230.61864	-161.61864	-1.230076887
7	12359.17225	196.82775	1.498052876
8	13788.2545	-122.2545	-0.930477021
9	12342.42167	67.578328	0.514337576
10	11723.04395	19.956049	0.151885168
11	12714.87566	-145.87566	-1.11025734
12	12905.50494	-94.504936	-0.719275561
13	13341.15068	180.84932	1.37644129
14	12452.77841	72.22159	0.549677369

Site 7 Regression

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.992292655
R Square	0.984644712
Adjusted R Square	0.890943751
Standard Error	127.1642251
Observations	14

ANOVA

	df	SS	MS	F	Significance F
Regression	3	11406284	3802094.619	235.1219	1.4365E-09
Residual	11	177878.14	16170.74015		
Total	14	11584162			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Time	-1211.014796	45.932735	-26.36496163	2.71E-11	-1312.11212	-1109.917477
Site 7 Init	0.983886642	0.0090132	109.1603679	4.77E-18	0.96404866	1.00372462
Pressure	130.4819205	45.700348	2.855162485	0.015652	29.8960808	231.0677602

RESIDUAL OUTPUT

Observation	Pred. Site 7 Final	Residuals	Standard Residuals
1	13954.54334	67.456655	0.530468809
2	12214.76431	118.23569	0.929787379
3	12122.27896	-41.278964	-0.324611454
4	11060.85065	-88.85065	-0.698707912
5	10344.12835	83.871651	0.659553828
6	12024.94475	-155.94475	-1.226325623
7	12198.03824	224.96176	1.769064879
8	13410.00121	-173.00121	-1.360454998
9	12176.39273	-130.39273	-1.025388464
10	11294.73422	-54.73422	-0.430421531
11	12387.92836	18.071643	0.142112631
12	12470.50427	-38.504274	-0.302791719
13	13275.49019	56.509814	0.444384525
14	12285.60415	113.39585	0.891727632

Site 8 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.99458575
R Square	0.989200814
Adjusted R Square	0.896328234
Standard Error	109.6488272
Observations	14

ANOVA

	df	SS	MS	F	Significance F
Regression	3	12114182	4038060.637	335.8651	2.4708E-10
Residual	11	132251.52	12022.86531		
Total	14	12246433			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Time	-1221.219172	39.485319	-30.92843648	4.79E-12	-1308.12582	-1134.312527
Site 8 Init	0.981228084	0.0077629	126.3989217	9.51E-19	0.96414194	0.998314223
Pressure	197.2703549	39.328871	5.015917084	0.000393	110.70805	283.8326597

RESIDUAL OUTPUT

Observation	Pred. Site 8 Final	Residuals	Standard Residuals
1	14022.71499	30.285013	0.276200064
2	12116.3129	-121.3129	-1.106376586
3	12180.09272	-14.092721	-0.128525958
4	10890.15241	-90.152408	-0.82219218
5	10382.60695	3.3930539	0.030944735
6	11831.20087	16.799128	0.153208463
7	12252.7036	108.2964	0.987665842
8	13379.76005	-196.76005	-1.794456486
9	12227.19167	12.808331	0.116812297
10	11232.48308	100.51692	0.916716764
11	12297.84009	-27.840091	-0.253902311
12	12469.12966	115.87034	1.056740383
13	13268.01798	154.98202	1.413439877
14	12330.22062	-95.220617	-0.868414372

Site 9 Regression

SUMMARY
OUTPUT

Regression Statistics	
Multiple R	0.97469809
R Square	0.950036366
Adjusted R Square	0.862539396
Standard Error	213.3734278
Observations	14

ANOVA

	df	SS	MS	F	Significance F
Regression	2	10388387	5194193.539	114.0873	4.4129E-08
Residual	12	546338.64	45528.21968		
Total	14	10934726			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
Time	-1163.144087	77.100236	-15.08612881	3.64E-09	-1331.13107	-995.157107
Site 9 Init	1.000074307	0.0132356	75.55961336	1.92E-17	0.97123648	1.028912129

RESIDUAL OUTPUT

Observation	Predicted Site 9 Final	Residuals	Standard Residuals
1	13923.97691	-36.976906	-0.173296679
2	12270.26754	-241.26754	-1.130729073
3	12173.26033	-4.2603304	-0.019966546
4	11270.0719	-186.0719	-0.872048144
5	10452.54598	120.45402	0.564522104
6	12281.26836	-351.26836	-1.646261014
7	12243.26553	366.73447	1.718744794
8	13303.46563	-24.465627	-0.114661075
9	12224.26412	-170.26412	-0.797963091
10	11286.07309	-29.073091	-0.136254504
11	12456.28136	-40.281359	-0.188783391
12	12332.27215	209.72785	0.982914588
13	13384.47165	72.528354	0.339912777
14	12331.27207	313.72793	1.470323332