A Systematic Approach and Framework for Optimizing a Polymer Sheet Manufacturing Operation

by

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and the Sloan Sloan School of Management in Partial Fulfillment of the
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and

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Abstract

A significant obstacle facing many U.S. manufacturing companies is the high levels of process variability and product waste that exist across their operations. Efficient manufacturing strategies can dramatically reduce process variability and product waste. These strategies can best be achieved through a systematic approach which:

- provides consistency of operation
- creates an invariant process and product
- increases quality product throughput
- works to minimize operations costs.

The focus of this thesis was to develop and implement a holistic manufacturing improvement strategy which targets process optimization efforts within a polymer sheet operation. In order to get to the root causes of the high process variability problem, this strategy must be universally applicable across all equipment and across the groups of personnel working to improve the operations. Critical steps are:

- **Diagnostic analysis and management of process equipment efficiency.** An asset utilization model was applied to a number of machines for diagnosis and management of process equipment efficiency. This model calculates an efficiency metric based on four manufacturing productivity parameters: availability, run speed efficiency, run time efficiency, and yield. The results show that increases made to the yield parameter could provide the largest improvement for the polymer operations by increasing quality sheet throughput and reducing waste. This process improvement provides additional manufacturing capacity of nearly 8%.

- **Diagnostic analysis and reduction of the manufacturing process variability.** A process optimization framework was developed relating process conditions to resulting product quality using the function-based process quality methods. This framework, using three parallel thrusts and a designed screening experiment, was developed and applied to determine key casting parameters and their effect on polymer sheet metrics. Capable product attribute data and their relative importance in determining overall product quality were established. A prediction model developed for a three month data set showed that key casting process parameters could determine if the resulting cast sheet was within the specifications allowed. This work is presented in a global manner to show the universal utility of this approach to a wide range of manufacturing processes.

Thesis Advisors: Tom Eagar, MIT, Department of Materials Science and Engineering
Jim Utterback, MIT, School of Engineering
Acknowledgements

My deepest appreciation and gratitude goes to my husband, Neal, and son, Kerrick, for their commitment, patience, love, and sacrifice over the last two years in allowing me to complete this program. A very special thanks goes to my parents for all of their encouragement and support throughout my life and for helping me out in those crazily stressful times.

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Chapter 1. Opportunities for Process Improvement and Waste Reduction

Optimizing the Manufacturing Process
One of the most significant hurdles facing many U. S. manufacturing operations is the high levels of process variability and product waste that exist across the production processes. Efficient manufacturing optimization strategies can dramatically reduce product variability while increasing quality product throughput or yield levels. These efficient optimization strategies can best be achieved through a systematic and widely applicable approach to minimizing process variability by creating an invariant process and product. The focus of this thesis is to develop and implement a systematic model which targets such manufacturing process optimization efforts to increase quality product yield and reduce waste within an polymer sheet manufacturing operation.

The manufacturing operation investigated here is a multi-step process. Polymer sheet production is distributed in parallel over a number of polymer machines. This production scheme offers several interesting opportunities for process optimization. Parallel production machines offer an excellent in-house (as opposed to external) opportunity for benchmarking. Additionally, parallel production machines are best optimized using a global optimization framework, since the optimization models developed in this manner will be the easiest to transfer among the different production machines employed.

Background on the Polymer Process
The casting process for manufacturing polymer sheet is based on original process and technology developed many years ago. This manufacturing operations is part of a vertically integrated company which manufactures most of the chemicals, raw materials, coatings, and base support necessary to produce a sensitized product for numerous photographic applications.

The polymer process is a continuous casting operation. A schematic example of a typical continuous casting process is shown in Figure 1.1. A viscous polymer stream is cast onto a wheel and conveyed through an oven system to create an polymer sheet of a specified thickness. Additional
Figure 1.1. Schematic diagram of a typical continuous casting operation.
coatings are applied to the polymer sheet during this process and vary in type and thickness depending upon the product being manufactured. This coated polymer sheet is wound into large rolls which are then sent to other operations within the Company. Some critical process features of the polymer sheet include thickness profile and uniformity across and down the sheet web, surface uniformity, absence of defects (i.e. holes, or inclusions), and sheet modulus. This thesis will focus on a set of polymer machines in one area of the sheet manufacturing operations.

**Process Improvement within the Operation**

This polymer sheet production operation is run by both operators and engineers. Teams of operators are responsible for operating the machines and performing the cleaning and basic maintenance of the equipment. A group of mechanics is assigned to and performs maintenance on the machines. Each team of operators is responsible for a group of machines. The process engineers are involved with process improvement activities for their group of machines. While every machine team is working on improvement activities, there are opportunities for additional cross-team involvement for sharing and learning among the various machine teams.

In addition to the machine teams mentioned above, process excellence teams (PETs) exist to drive continuous improvement activities by machine function. The PETs include engineers working within the polymer operations. There are several PETs covering functions such as casting, coating, winding, and conveyance. While this approach has yielded near term improvements in individual aspects of the production process, these teams are primarily working on specific functional areas of the overall production process.

Even though these two groups, the machine teams and the PETs, are working on machine-based or functional area-based process improvement efforts, there has been little activity to investigate process improvement strategies on a global scale, across all machines, and through the benefit of systematic and holistic operating practices. Process improvement activities have been primarily driven by machine-specific problems. It has been often
observed that the same product manufactured on different machines may result in different product characteristics.

**Systematic Approach for Improving the Manufacturing Process**

In order to get to the root causes of the high process variability problem, a systematic and holistic manufacturing improvement strategy must be implemented to achieve the increases in quality throughput and reductions in costly waste that are needed to optimize manufacturing productivity. These common tools (metrics) and systematic strategies must be universally applicable across all equipment and across the numerous groups of personnel working to improve the manufacturing process (Figure 1.2). Key steps critical to the development of this model are:

- Diagnostic analysis and management of process equipment efficiency and effective utilization
  - asset utilization model

- Assessment and management of the manufacturing process variability and its sources
  - Function-Based Process Quality (FAB-PQ) approach
  - designed experiments

- Systematic analysis of process-product relationships
  - data acquisition and reduction
  - canonical discriminant analysis
  - predictive model development

- Definition and management of important product quality attributes and their measurement
  - product metrics
  - capable testing procedures
  - standardized sampling practices

These key steps will be presented in this thesis in a global framework to emphasize the universal utility of this approach to a wide range of
Figure 1.2. Creating linkages and common tools across the manufacturing operation for continuous improvement activities
manufacturing processes. The development and application of these tools will be discussed in the subsequent chapters of this thesis.

**Highlights of the Manufacturing Optimization Framework**

An asset utilization model for diagnosis and management of process equipment efficiency was applied to a number of polymer machines. This model, discussed in Chapter 2, calculates an efficiency metric based on four manufacturing productivity parameters: availability, run time efficiency, run speed efficiency, and yield. The results of the asset utilization model allowed for unambiguous targeting of optimization efforts by showing that the yield parameter could provide the largest process improvement by increasing quality sheet throughput and reducing waste. Improving the yield numbers across all of the machines essentially provides a significant manufacturing capacity gain of 8%. This capacity gain is achieved by improving the yield parameter alone. Additional gains can be achieved through the other three parameters as well. This will be discussed in Chapter 4.

A process optimization framework was developed relating process conditions to resulting product quality using the FAB-PQ methods. This process optimization framework was applied to the analysis of the casting process and its relationship to the cast polymer sheet attributes by using three parallel thrusts of knowledge and experience, statistical process data, and theoretical calculations to determine the key casting parameters and their effect on polymer sheet metrics. A prediction model, developed with process data and product attribute data, demonstrated that key casting process parameters could determine if the resulting cast polymer sheet was within the allowed specifications. This work also allowed for systematic characterization and documentation of the process variables affecting final product attributes. The parallel activities and findings will be presented in Chapter 3.

As a result of the parallel activities and outcomes of these activities, a screening experiment was conducted on the casting process to assess casting process parameters critical to producing quality cast polymer sheet. An important part of this effort was developing capable product metrics to
quantify the cast polymer sheet attributes and establishing the relative importance of these attributes in determining overall product quality. These results will be discussed in Chapter 4.

The utility and application of this holistic strategy and framework for improving manufacturing productivity performance of the polymer process and other manufacturing processes will be reviewed in Chapter 5.

Manufacturing Laws
Four manufacturing laws evolved from this work will be presented in Chapter 5. They are as follows:

- Metrics must be independent and true measures and must be easily understandable
- Performance incentives that encourage modification of the metrics must be prohibited
- Single measures of product are not sufficient to properly quantify the product quality
- Multivariate statistical techniques provide insight into the state of the process, serving to predict product quality.
Chapter 2. Model for Examining Asset Utilization

Asset Utilization Model
• Definition and scope
Increasing the productivity and efficiency of manufacturing operations is significant, if not vital to improving overall product quality and reducing manufacturing costs. As a company strives to increase its financial performance and maintain a competitive advantage, a systematic approach is needed to assess how effective the capital assets are being used. A holistic framework developed by F. Stewart, the asset utilization model, examines manufacturing asset parameters and determines how efficiently the equipment produces quality output on a continuous timeframe (1-3). An important aspect of this model is its applicability to a wide range of manufacturing operations. A primary goal of this thesis is to apply and demonstrate the impact of this model on an web manufacturing facility.

The asset utilization model described in this chapter examines four key manufacturing productivity parameters: availability, run time efficiency, run speed efficiency, and yield. These parameters are listed and defined in Table 2.1. Each of the parameters looks at a

<table>
<thead>
<tr>
<th>Table 2.1. Definition of Asset Utilization Model and Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asset Utilization = Availability X Run Time Efficiency X Run Speed Efficiency X Yield</td>
</tr>
<tr>
<td>Availability = % of time that the equipment is available to run</td>
</tr>
<tr>
<td>Run Time Efficiency = % of the total production cycle time spent running</td>
</tr>
<tr>
<td>Run Speed Efficiency = % of the maximum speed achieved</td>
</tr>
<tr>
<td>Yield = % of the run time that quality product is produced</td>
</tr>
</tbody>
</table>

specific part of a manufacturing process infrastructure. The availability calculation determines the percent of time in a calendar year that the equipment is available to run product. Time spent on maintenance and idle time due to lack of customer orders would be tracked by this metric. The run time efficiency metric examines the percent of cycle time that is spent actually running product. The amount of cycle time spent on setup
practices and product change requirements would be accounted for in this measurement. The run speed efficiency calculation looks at current equipment operation speed and compares it to the maximum equipment operating speed rating. The yield calculation determines how much time quality product is manufactured during the available run time.

An asset utilization number is obtained by multiplying the four manufacturing productivity parameters together. Initially, the asset utilization number is viewed as a baseline for the manufacturing equipment. Through benchmarking activities, internal and external, asset utilization numbers can be obtained to serve as benchmarking standards. These internal and external benchmarking standards can serve as five year goals for continuous improvement activities as the manufacturing operations strive to achieve and maintain world class manufacturing capabilities.

Application to the Polymer Operations

- **Asset utilization calculations**

The asset utilization model and manufacturing productivity parameters are a common and consistent method for examining the capability of each polymer machine to produce quality product effectively. A breakdown of each calculation is shown in Table 2.2.

<table>
<thead>
<tr>
<th>Table 2.2. Calculation of Four Manufacturing Productivity Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Availability = (Total time - (Scheduled+Unscheduled maintenance+Idle time)) / Total time</td>
</tr>
<tr>
<td>Run Time Efficiency = Run time / (Run time + Setup time)</td>
</tr>
<tr>
<td>Run Speed Efficiency = Average run speed / Installed speed</td>
</tr>
<tr>
<td>Yield = Time quality output is produced / Run time</td>
</tr>
</tbody>
</table>

Availability is the percent of time the equipment is available to run. To calculate availability, the amount of time spent on scheduled and unscheduled maintenance must be obtained for the calendar year. Additionally, the amount of time that the equipment was idle due to lack of customer demand must be determined.
Run time efficiency is the percent of production cycle time that the equipment is running. To calculate the run time efficiency, time associated with setup must be obtained for the calendar year.

Run speed efficiency is the actual operation speed of the equipment versus the maximum installed machine speed. The theoretical speed can be determined by the part of the process which is the speed limiting step or bottleneck for the operation. Another approach would be to take 80% of the maximum speed recommended for equipment operation.

Yield is the percent of the run time that quality product is manufactured on the equipment. To calculate yield, the amount of time spend running waste, conducting experiments, or running substandard product must be assessed.

**Results and Discussion**

* Parameter calculations for the polymer machines
  Asset utilization calculations were performed on a group of the polymer machines within the sheet manufacturing operations. Data obtained from the parameter calculations for eight polymer machines are shown in Tables 2.3, 2.4, 2.5, and 2.6. Example calculations have been worked up for two machines to show monthly data. Calculations for all parameters except run time efficiency were obtained on a monthly basis for the first nine months of 1992. Run time efficiency calculations were performed on total data for the nine month period.

Availability values ranged from 64.3 to 96.5%. Scheduled maintenance, unscheduled maintenance, and idle time due to lack of customer orders affect this metric. Most of the unavailable equipment time was unscheduled maintenance and scheduled downtime. There was little idle time across the polymer machines evaluated in this work.

Run time efficiency values approached 100%, ranging from 94.7 to 99.1% for the polymer machines studied. High values were expected for run time efficiency since the polymer sheet manufacturing process is a continuous
Table 2.3. Availability calculations from January through September 1992

\[
\text{Availability} = \frac{\text{Total Hours} - (\text{Scheduled} + \text{Unscheduled Maintenance} + \text{Idle Time})}{\text{Total Hours}} \times 100
\]

<table>
<thead>
<tr>
<th></th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sept</th>
<th>9-M Ave</th>
</tr>
</thead>
<tbody>
<tr>
<td>machine C %Avail</td>
<td>92.98</td>
<td>78.42</td>
<td>86.88</td>
<td>100</td>
<td>100</td>
<td>86.16</td>
<td>52.44</td>
<td>81.7</td>
<td>23.38</td>
<td>78.08</td>
</tr>
<tr>
<td>machine D %Avail</td>
<td>97.79</td>
<td>100.00</td>
<td>95.89</td>
<td>77.49</td>
<td>100.00</td>
<td>87.53</td>
<td>97.00</td>
<td>100.00</td>
<td>98.36</td>
<td>94.94</td>
</tr>
</tbody>
</table>

Machine #  F  G  H  I  M  O
% Availability*  64.26  95.14  81.04  93.29  86.33  96.55

* Availability values are the 9 month averages
Table 2.4. Run Time Efficiency Calculations from January through September 1992

Run Time Efficiency \(= \frac{\text{Actual Footage}}{\text{Actual Footage} + \text{Setup Footage}} \times 100\)

<table>
<thead>
<tr>
<th>Machine #</th>
<th>C</th>
<th>D</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>M</th>
<th>O</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Run time efficiency*</td>
<td>95.81</td>
<td>98.65</td>
<td>94.68</td>
<td>98.38</td>
<td>96.11</td>
<td>97.92</td>
<td>96.96</td>
<td>99.11</td>
</tr>
</tbody>
</table>

* %Run time efficiency values are the 9 month average

Table 2.5. Run Speed Efficiency Calculations for January through September 1992

Run Speed Efficiency \(= \frac{\text{Average Run Speed}}{\text{Installed Speed}} \times 100\)

<table>
<thead>
<tr>
<th>C</th>
<th>D</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>M</th>
<th>O</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Run speed efficiency*</td>
<td>74.71</td>
<td>87.54</td>
<td>73.80</td>
<td>83.97</td>
<td>91.24</td>
<td>96.70</td>
<td>85.05</td>
</tr>
</tbody>
</table>

* %Run speed efficiency values are the 9 month average
Table 2.6. Normalized Yield Calculations for January through September 1992

Yield = (Hours Quality Sheet Produced / Run Time) * 100

<table>
<thead>
<tr>
<th>Month</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sept</th>
<th>9-M Ave</th>
</tr>
</thead>
<tbody>
<tr>
<td>machine C</td>
<td>%Yield</td>
<td>0.75</td>
<td>0.58</td>
<td>0.69</td>
<td>0.99</td>
<td>0.94</td>
<td>0.89</td>
<td>0.75</td>
<td>0.73</td>
<td>0.86</td>
</tr>
<tr>
<td>machine D</td>
<td>%Yield</td>
<td>0.94</td>
<td>1.03</td>
<td>0.93</td>
<td>0.79</td>
<td>1.09</td>
<td>0.99</td>
<td>0.99</td>
<td>0.98</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Machine #  
F  
G  
H  
I  
M  
O  

% Yield*  
0.78  
0.92  
0.87  
0.90  
1.00  
0.99

* Normalized yield values are the 9 month averages
casting operation with a large number of machines. Consequently, there are minimal product changes on the machines.

In order to perform the run speed efficiency calculations, the machines were evaluated as either type 1 or type 2 machines. There are tradeoffs of speed and product characteristics between the two types of machines.

For the run speed efficiency calculations, type 1 machines are speed limited by the process equipment. This speed limitation was used as the maximum possible run speed for the type 1 machines. The type 2 machines are limited by both the product type and thickness specifications of the film base product being produced on each machine. The maximum possible run speed for the type 2 machines was based on the speed limitations imposed by product specifications. The run time for each machine was multiplied by the maximum speed to get the maximum achievable footage for each machine. The maximum footages were compared with the actual footages on a monthly basis over a nine month period to determine the run speed efficiencies. Run speed efficiency values ranged from 73.8 to 96.7%.

Yield values among the machines ranged from normalized values of 0.75 to 1. The total time spent running machine waste, discarded materials, experiments and charge hours were taken from the run time for each machine on a monthly basis to obtain the time each machine produced quality product.

*Comparison to the Company reliability calculation*
Currently, a reliability metric is used within the Division as part of the Company-wide quality improvement activities. This reliability calculation divides the time spent making good product by the sum of the scheduled run time and charge hours as opposed to the yield calculation of the asset utilization model which divides the quality product hours by the run time. Table 2.7 compares the yield parameter calculated by the asset utilization model with the reliability parameter for machine C over a nine month period. These calculations provide similar results with the reliability numbers being slightly lower than the yield numbers. Even though the
Yield = quality product hours / run time
Reliability = good product hours / (scheduled run time - charge hours)

<table>
<thead>
<tr>
<th>Month</th>
<th>Yield</th>
<th>Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.75</td>
<td>0.70</td>
</tr>
<tr>
<td>2</td>
<td>0.58</td>
<td>0.51</td>
</tr>
<tr>
<td>3</td>
<td>0.69</td>
<td>0.68</td>
</tr>
<tr>
<td>4</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>5</td>
<td>0.94</td>
<td>0.97</td>
</tr>
<tr>
<td>6</td>
<td>0.89</td>
<td>0.82</td>
</tr>
<tr>
<td>7</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>8</td>
<td>0.73</td>
<td>0.59</td>
</tr>
<tr>
<td>9</td>
<td>0.86</td>
<td>0.70</td>
</tr>
</tbody>
</table>

9 month average 0.81 0.75

numerical differences are small, the way in which the two parameters are determined is quite different.

The differences between the two calculations occurs in the way in which the denominator is defined. The yield calculation in the asset utilization model uses the actual machine run time as its denominator. The actual run time is determined from the availability calculation and is based on subtracting the scheduled and unscheduled maintenance and the idle time from the calendar time. This is the actual time that the machine has available for manufacturing a quality product.

Under the Company reliability calculation, the denominator is the scheduled run time. The scheduled run time is based on subtracting the scheduled maintenance time and charge hours from the calendar time. The reliability calculation uses portions of indices covered in the availability and yield asset utilization calculations, however, this is done incompletely. For example, the reliability calculation penalizes machines for unscheduled down times by not deducting those hours from the denominator. Yet, charge hours, which have nothing to do with the amount of time the equipment is available to run, are subtracted out of the
denominator. The charge hours have already been accounted for in the numerator in determining the good or quality product hours. The reliability parameter does not independently measure the percent of run time that quality product is made but instead measures the percent of time quality product is made as determined by scheduled down times and charge hours. These measures confound an unbiased calculation of available hours.

**Advantages of the Asset Utilization Model**

• **Independent manufacturing productivity parameters**

A significant advantage of the asset utilization model is that the manufacturing productivity parameters are assessed on an independent and individual basis. The yield parameter measures only the amount of time spent producing quality product. The run time efficiency parameter solely addresses the effect of set up time on the production cycle time. The availability parameter specifically calculates the time the equipment is available to run product. The run speed efficiency parameter compares the operating speed with the maximum allowed speed.

Since these parameters focus on specific and independent areas of equipment utilization, continuous improvement activities can be easily pinpointed and defined for each parameter. Figure 2.1 highlights this unique feature. For example, the causes of a low availability number can be readily identified by examining the hours attributed to scheduled downtimes, unscheduled maintenance, and idle time due to lack of customer orders. If unscheduled maintenance time is the largest contributor to the low availability number then an operations plan can be developed to scrutinize the unscheduled maintenance causes and delineate the improvement activities and maintenance practices needed to reduce the unscheduled maintenance hours.

Similar scenarios could be enacted if the scheduled downtimes or the idle times were the significant contributors to the low availability number. Similar approaches could be developed for the other manufacturing parameters such as yield, run time efficiency, and run speed efficiency.
Figure 2.1. The asset utilization model as a driver for manufacturing improvement activities.

How efficiently is capital equipment being utilized?

Asset Utilization Number = A * RSE * RTE * Y

Availability
- maintenance & repairs
- scheduled downtime
- idle time due to lack of customer demand

Run Speed Efficiency
- equipment operating speeds

Run Time Efficiency
- setup time

Yield
- machine waste
- discards & rejects
- experimentation

Potential areas for improvement
unscheduled downtimes
maintenance times
inadequate customer orders

slow operating speeds

product change times
setup times

product variability
inadequate process control
product testing methods
**Linkage with business unit goals**

Most importantly, the asset utilization model and parameter calculations serve as a common method and metric for examining the capability of manufacturing equipment to produce quality product effectively across all business unit activities. The four asset utilization parameters help the operators, engineers, and managers work together to assess various parts of the operations, examine existing equipment and operating practices, and pinpoint areas for improvement.

In addition to using the manufacturing productivity parameters as metrics in manufacturing improvement activities, the asset utilization model can be linked with a manufacturing operation's five year business goals serving as the driver for identifying improvement opportunities. The costs and benefits associated with these opportunities can be established for incremental increases in the asset utilization parameters and overall number. Figure 2.2 shows these linkages.

A clearly defined five year business plan might target goals of improving quality, increasing throughput, maximizing profit, and reducing costs. The asset utilization numbers and productivity parameter numbers identify opportunities that directly link to these targeted business goals within the manufacturing operation. Cost-benefit analyses help to prioritize and select improvement efforts, by determining the cost and benefit tradeoffs associated with an incremental increase of X% for any of the four manufacturing productivity parameters. The cost of achieving the desired business goal improvement and, subsequently, the asset utilization number increase can be assessed as $Y while the benefit of the increase can be projected as $Z. A thorough utilization analysis of equipment efficiency and the results of cost-benefits analysis combine to give the manufacturing operation focused and knowledge-driven improvement activities which provide favorable throughput and quality gains in a cost effective manner.

**Benchmarking Approach**

- **Practice for company class standard**

Within the polymer operations, the asset utilization parameters and calculations can drive process improvement activities and programs by
Figure 2.2. Identifying and prioritizing improvement opportunities with the asset utilization model.

Statement of Goals

5 year Business Plan
Goals might include:
- quality improvements
- throughput increases
- profit maximization
- cost reductions

Identifier for Opportunities

Asset utilization model as driver for identifying continuous improvement opportunities

\[ AU\# = A \times RSE \times RTE \times Y \]

Prioritization Process

Prioritization and parameter selection for 5 year business plan goals

- Availability
- Run Speed Efficiency
- Run Time Efficiency
- Yield

Cost-Benefit Analysis

For an incremental increase, X%, of a selected parameter:
- cost of accomplishing the increase can be assessed as $Y
- benefit of the increase can be projected as $Z
initially focusing on the machines with the lowest asset utilization numbers. As noted in Chapter 1, the large number of parallel polymer machines provides a unique internal opportunity for benchmarking. Best practices on polymer machines with high asset utilization numbers can be analyzed, dissected, and applied to the other machines for improved operation and efficient performance.

As an approach to internal benchmarking, the calculations for the polymer machines studied in this model were separated into two categories - one for type 1 machines and one for type 2 machines. An internal benchmarking standard was determined for each machine type category by taking the numerical value of the best machine for each manufacturing productivity parameter and multiplying these numbers together to get an overall composite asset utilization number. For the type 1 machines, as shown in Table 2.8, a normalized asset utilization composite number of 0.96 was obtained for use as the type 1 internal benchmarking standard. Asset utilization numbers ranged by approximately 0.45 across the four type 1 machines. For the type 2 machines, as shown in Table 2.9, an asset utilization composite number of 0.81 was obtained as the type 2 internal benchmarking standard. Asset utilization numbers ranged by approximately 0.45 across the four type 2 machines. The asset utilization manufacturing productivity parameters in Table 2.8 and 2.9 have been put into bar charts for ease of viewing in Figures 2.3 and 2.4.

- **Recommendation for external benchmarking**

Information on competitors processes is difficult to obtain, especially data on the amount of generated waste, downtime, idle time, and maintenance hours. An alternative approach proposed herein is to examine other web manufacturing processes within the Company or non-competitive web manufacturing processes external to the Company such as aluminum rolling for further insight into methods and practices that could be applied to the continuous improvement of polymer sheet manufacturing. It is very likely that another non-competitive manufacturer, would be amenable to cross-benchmarking in this manner since both organizations would stand to benefit from this interaction. Additionally, external benchmarking
### Table 2.8. Internal Benchmarking Standard for Type 1 Machines

<table>
<thead>
<tr>
<th>Type 1 Machines</th>
<th>Availability</th>
<th>Run Time Efficiency</th>
<th>Run Speed Efficiency</th>
<th>Yield</th>
<th>Asset Utilization</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
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<td>0.97</td>
<td>0.85</td>
<td>0.75</td>
<td>0.50</td>
</tr>
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<td>1</td>
<td>0.97</td>
<td>0.96</td>
</tr>
<tr>
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<td>0.97</td>
<td>1</td>
<td>0.87</td>
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</tbody>
</table>

Type 1 Machine Standard for Asset Utilization = 0.99 x 1 x 1 x 0.97 = 0.96

---

### Table 2.9. Internal Benchmarking Standard for Type 2 Machines

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<thead>
<tr>
<th>Type 2 Machines</th>
<th>Availability</th>
<th>Run Time Efficiency</th>
<th>Run Speed Efficiency</th>
<th>Yield</th>
<th>Asset Utilization</th>
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</thead>
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<tr>
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<tr>
<td>O</td>
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<td>1</td>
<td>0.82</td>
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</tbody>
</table>

Type 2 Machine Standard for Asset Utilization = .97 x .99 x 1 x .91 = .87
would allow for the assimilation of innovations that would not be observed in the internal benchmarking activities.

Focus for the Asset Utilization Calculations

• Areas for improvement

Based on the asset utilization model calculations presented Tables 2.8 and 2.9, the manufacturing improvement activities of my thesis will focus on increasing machine yield for the following reasons:

• Run time efficiencies are high, averaging approximately 97% for the machines studied. With a large number of machines in operation, machines can be dedicated to making specific products. Set up times and product changes are minimized.

• Availability numbers rank second to run time efficiency numbers averaging approximately 87% across the machines studied. A preventive maintenance and equipment reliability program would help to improve the availability numbers.

• Yield numbers and run speed efficiency numbers were the two lowest parameters for most machines. Increasing these parameters clearly would have the greatest effect on increasing polymer sheet throughput. Process improvement activities would improve both of these numbers.

• Increasing run speed would increase throughput and run speed efficiency but would adversely affect product quality, (as per prior machine experience), which would contribute to even lower yield numbers.

• Yield improvements would increase throughput by increasing the amounts of quality product produced. An increase in the asset utilization number would also result from increasing yield parameter.

Improving yield through a systematic process optimization framework would serve to reduce high levels of process variability and product waste
across the machines. Methods and operating practices developed through the process optimization framework would not only improve the yield numbers but would put the engineers and operators in a better position to address the speed issues since the process would be well characterized.

Once an asset utilization parameter is identified as a focus area, such as the yield parameter for the polymer operations, the focus area must be broken down into specific improvement opportunities so that action plans can be developed. For the yield parameter, pareto diagrams were examined to determine where the process optimization framework should be initially directed. Examining a pareto breakdown of product waste categories for machine C (Figure 2.5) shows that approximately 60% of all waste can be

![Figure 2.3. Pareto breakdown of waste for machine C](image)

related to the casting process. Casting process, practices, and casting equipment and process conditions will be the focus of the process optimization activities discussed in this thesis.
Chapter 3. Framework for Optimizing the Manufacturing Process, Part I: Three Parallel Activities

Process Optimization Framework

• The need for process and product variability reduction

The asset calculations for the polymer machines, outlined in Chapter 2, indicate that the yield parameter is the best focus for manufacturing productivity improvement activities as developed in this thesis project. Increasing the amount of quality sheet throughput and reducing the amount of waste will improve the overall manufacturing productivity of the polymer operations as well as reduce operating costs.

In a survey conducted in early 1992 of the engineers and operators associated within the polymer operations, the casting and coating processes were identified as the areas of greatest variability (4). Examining pareto breakdowns for the types and magnitudes of waste generated across the polymer machines show that approximately 60% of the polymer sheet waste conditions can be attributed to the casting process. Activities developed as a part of this internship project for improving the yield manufacturing productivity parameter will be focused on improving operational practices for the polymer sheet casting process.

One mechanism for leveraging process improvement activities is to assess the operational similarities and differences across all of the polymer machines, especially among those machines producing the same product type. If a process improvement approach can be developed that is applicable in general terms for common machine functions then it can be more easily and efficiently applied to all machines in terms of manpower, time and cost. Likewise, this approach should also be adaptable to additional tailoring to compensate for machine-to-machine differences.

The Function-Based Process Quality (FAB-PQ) approach developed by R. Grant (5,6) meets these challenges. FAB-PQ is a systematic method for examining and reducing process variability. A particularly attractive feature is its function-based focus for systematic process characterization.
A major goal of this internship project is to develop and apply a process optimization framework as a part of FAB-PQ for the *process-product* relationship as shown in Figure 3.1. An important sub-goal of this thesis is the predictive analysis of the process-product relationship. This approach to process characterization and optimization is unprecedented, since the development and application of the FAB-PQ approach prior to this thesis had focused solely on *process-process* relationships, wherein function-based verification strategies are not directly related to product quality. Both of these types of relationships will be discussed in more detail below.

The process optimization framework developed in this thesis quantifies the relationship between process conditions and the resulting product attributes. Because of the high levels of waste associated with the casting process, the casting signals, conditions, practices, and the cast sheet attributes will be the focal points (or inputs) of this framework. A prediction model, developed as an output of this work, will be employed to demonstrate that the process signals and conditions can be used to predict whether or not the resultant cast polymer sheet will have mean thickness and profile metrics within specification.

**The FAB-PQ approach and definition**

The FAB-PQ approach was chosen in late 1991 as a divisional activity to improve the polymer manufacturing process. A polymer machine was selected as the platform for this activity with the idea that once the FAB-PQ method was developed and demonstrated on one machine for reducing process variability, then the method would serve as a model for the other polymer machines. The overall objective of the FAB-PQ method is to continuously maintain an invariant process and provide consistent product quality. A flowchart for FAB-PQ is shown in Figure 3.2. The FAB-PQ approach strives to:

- facilitate process understanding and characterization
- efficiently detect and resolve process problems
- develop a reliable, robust process model
- reduce product variability by reducing process variability
Figure 3.1. Approach for a process improvement model.

- Model applicable to all polymer machines
  - general for common functions
  - tailor for machine differences

- FAB - PQ
  - functional flow analysis
  - verification strategies

- process - process relationships
- process optimization framework
- process - product relationships
Figure 3.2. A flowchart for the FAB-PQ approach.

Inputs
Customer Needs
Process Problems
Causes of Waste
Productivity Issues
Cycle Time
Other...

1. Vision
   - Five year future state
   - Where to begin?
2. Process Scope
3. Functional Flow
   - The functional perspective
4. Function Definition
   - Most critical customer
   - Product specifications
   - Process capability
5. Process Control
   - What is run to target?
   - How is it kept there?
   - What is the target?
6. Process Verification
   - What can go wrong?
   - How will I know?
7. Implementation
   - Procedures, CAGS
   - Learn about process
8. Process Optimization
   - Find product-process links
   - Optimize control strategies

Taken from R. P. Grant (8).
The FAB-PQ approach incorporates unique features that make it different and more broadly encompassing in scope than other process optimization approaches previously studied or documented in the literature. These novel features (5-8) are:

- functional flow analyses which break down manufacturing processes into small subprocesses called functions
- verification strategies for each function which serve as integral elements of the process optimization
- continuous use of verification strategies to determine in real time whether or not the process is in an invariant state.

In the FAB-PQ approach, a manufacturing operation is first divided into subprocesses called functions. A typical functional flow diagram is shown in Figure 3.3 for the polymer casting process. The functions must be defined at a level such that each function can be viewed and analyzed as a separate manufacturing process. The functions are defined as transformations of the process rather than components or parts of equipment (4,5). Each function is analyzed so that the inputs and outputs of the function can be characterized and their relationships understood.

Next, strategies for process control, verification, and optimization are developed, tested, and implemented at the operational level for each function. Numerous process optimization approaches used in manufacturing operations today and those cited in research journals typically lack the verification strategy approach and include only the process control and optimization steps.

Verification strategies insure that process disturbances and sources of process variability within each function are continuously identified and made clearly visible during operation. With only overall process control strategies in place (as opposed to functional verification strategies), it is difficult to insure that the process remains invariant during operation. Process conditions are continuously monitored through the verification strategies, so that problems and disturbances can be detected. Typical problems and disturbances that might occur include process condition changes, measurement instrumentation drift and failure, equipment

35
malfunctions, and variations in incoming material quality and consistency.

The FAB-PQ work performed prior to this thesis had focused on functional analysis and verification strategy development for the process-process relationship. An example of a function with process inputs and process outputs is shown by the cool polymer function in Figure 3.3. In this function, the polymer stream is cooled to a specific and consistent temperature. The inputs for the function are the incoming polymer stream temperature and the initial water temperature circulating through the cooling system. The outputs for the function are the resulting polymer stream temperature and the exiting water temperature. The algorithm developed as the verification strategy might check the four temperatures to ensure that they are within specified ranges and that there is no drifting occurring or a major change in any of the four parameters. The rate of temperature change would be evaluated against past data. The algorithm would also calculate the differences in the water and polymer temperatures based on heat transfer properties, and determine that the rate of temperature change is within an allowable tolerance. This verification strategy would continually insure, in a rapid manner, that there are no process disturbances or problems occurring with the equipment, sensors, or incoming materials. Thus, a functional analysis and verification strategy developed for the process-process relationship is appropriate and satisfactory for this function. It is important to note however, that no relationship is established with final product attribute data.

- Verification strategies for the process-product relationships

As we work our way through the casting functional flow diagram in Figure 3.3, we come to two functions for the casting hopper which are highlighted in the gray box. The casting hopper is the continuous casting equipment. The two casting functions critical to the sheet casting operation, are:

- distribute flow of polymer in the hopper
- shape the catenary between the hopper slot and the wheel surface.
Figure 3.3. Functional flow diagram for the casting process.
The polymer sheet thickness profile and edge shape result from the casting process conditions that are a part of these two functions. Analysis of the process-process relationships for these two functions does not verify the cast polymer sheet attribute parameters and will not validate that the cast sheet parameters are within specific limits. Therefore, the verification strategies for these two casting functions must include algorithms that capture the process-product relationships. The process optimization framework of this thesis was developed for just this purpose, i.e. to address the process-product relationships.

A schematic diagram of the casting zone is shown in Figure 3.4. The viscous polymer stream flows into the casting hopper reservoir at a specific temperature and viscosity. The polymer flows from the casting hopper reservoir through a slot of fixed dimensionality, forming a catenary in the distance between the hopper slot and the wheel surface. The two casting functions, 1) distribute flow and 2) shape catenary, are the first steps in creating the polymer sheet. The inputs and outputs of each function are listed in Figure 3.5 as the incoming polymer stream is cast to form polymer sheet. These functions directly and dramatically affect the final polymer sheet (i.e. final product) properties and quality such as the cross web thickness, thickness profile, and edge conditions.

A typical thickness profile from a widthwise polymer sheet sample is shown in Figure 3.6 and resembles a smile configuration. Examining the product metrics of target sheet thickness, widthwise thickness profile, and edge shape determines whether or not the sheet is within the product specified ranges. Variations in these metrics due to casting process conditions can occur across and down the sheet direction. The magnitude of the effects of process conditions encompassed by these functions (Figure 3.5) relate directly to final product metric data and can be used to develop mathematical models for identifying those state-of-control surfaces which occur under natural production conditions that give rise to good product.

This process optimization framework extends the applicability of FAB-PQ in a novel manner, encompassing the characterization of process-product relationships. The framework utilizes three parallel activities to
Figure 3.4. A schematic diagram of the casting zone.
Figure 3.5. A functional breakdown of the two casting functions: distribute flow and shape catenary.
Figure 3.6. Thickness profile for a widthwise polymer sheet sample at normal operating conditions.
systematically study and select key casting process parameters by determining the affect of the casting conditions on polymer sheet metrics. From this point on, the discussion of the process optimization framework and methods will apply solely to the process-product relationship as a means of reducing process and product variability and increasing quality sheet throughput.

**Examining the process-product relationship in parallel activities**

The process optimization framework is outlined in Figure 3.7. The framework is a unique addition to the FAB-PQ approach in that it focuses on the process-product relationship. The framework proposed here characterizes and quantifies the cause and effect relationship between casting process conditions and the resulting polymer sheet product attributes. These parallel activities serve to better characterize the two casting functions identified for study in this thesis from three points of reference:

- first-hand knowledge and experience
- existing process data examination
- order-of-magnitude theoretical calculations

The purpose of the three parallel activities is to identify, in a holistic and systematic manner, the key process parameters and practices that most significantly affect the casting of polymer sheet. The key parameters and practices obtained from these activities were incorporated into a designed screening experiment to assess the first-order or main effects of these parameters on cast sheet. The information derived from these activities helped to generate parameters and algorithms to serve as verification strategies for predicting, in a real time manner, that the process and resulting product are invariant.

The experience and knowledge of the personnel within the polymer operations provided an opportunity to collect valuable in-depth information about the casting process. Examination of historical data from the casting process with statistical multivariate techniques helped in quantifying the relationships between casting signals and product test data. Order-of-
Figure 3.7. The process optimization framework developed for examining the process-product relationships.

- On-going parallel efforts
  - Knowledge / experience
    - Key parameters based on knowledge and opinion
  - Process data
    - Key parameters based on statistical analyses
  - Theoretical calculations
    - Key parameters based on theoretical calculations

- Experimental selection of key parameters
- Prediction model for casting operation
magnitude theoretical calculations served to prioritize the casting signals and signal levels that had the greatest effect on the product test data.

**Knowledge and Experience**

- **Approaches for collecting information and knowledge**

  Valuable resources for gathering information about the casting process and selecting key casting parameters were the engineers, operators, and maintenance personnel working on the polymer machines. Brainstorming sessions, interviews, and one-on-one discussions were used to collect the knowledge and experience of these people in gathering pertinent information about the casting process and practices.

  During the brainstorming sessions, open discussions regarding potential problems associated with casting took place. The casting process, conditions, and practices were interrogated as to their effect on polymer sheet quality. Nine potential product conditions related to the casting process were highlighted. Three were selected by group members as the ones which occurred most frequently in the cast polymer sheet. The three product conditions are:

  - widthwise thickness variation in polymer sheet
  - longitudinal thickness variation
  - edge condition variability

  As shown earlier in Chapter 3, a typical widthwise thickness profile, depicted in Figure 3.6, results from casting conditions highlighted in Figure 3.5. A widthwise sheet sample can be considered out-of-specification based on criteria for thickness target, widthwise thickness profile, and edge profile. Variations in thickness can occur down the sheet or longitudinally as well as across the sheet or in the widthwise direction.

  Negligible changes in the thickness profile in the longitudinal direction are desired. Yet, over time and with changing casting conditions, thickness can vary longitudinally. The edge condition and profile are important for overall sheet profile. It is also important that the edges on each side of the sheet have similar profiles. Finally, it is important that the edges have
sufficient thickness and shape so that they do not tear off during other steps in the process. Information was gathered on the casting process and the polymer sheet quality attributes as the first step in examining cause and effect relationships.

Fault tree diagrams were used as tools to visualize and organize the information generated in the brainstorming sessions. These diagrams served to capture the various opinions, knowledge, and experience of the group and helped to understand the relationship between the casting process and the conditions associated with undesirable product quality. An example of one of the fault tree diagrams is shown in Figure 3.8 for the variability in the polymer sheet thickness profile.

Figure 3.8 shows only a portion of the complete fault tree diagrams generated for the casting and coating processes. Different opinions about waste causes and process practices were collected, grouped, and assembled using the fault tree tool to systematically view the root cause and relationship effects for the casting and coating processes. The final composite fault tree diagrams for each process were large and lengthy diagrams that are, at this operation, used for process discussion, selection of improvement focus by area, experimental design, training purposes, and corrective action guidelines for troubleshooting. In essence, the development of extensive fault tree diagrams for this process is a valuable exercise in gathering together the knowledge and learnings of experienced personnel so often lost or not captured. These diagrams will serve many purposes beyond the scope of this thesis.

Rankings of the casting process conditions and practices were obtained from the group of engineers, operators and maintenance people based on their experience and knowledge in examining casting-related product quality problems. The process conditions and signals believed to have the greatest influence on cast sheet attributes were those related to pressure and thermal conditions. Signals such as casting valve pressure, filter pressure, casting hopper temperature and the polymer stream temperature were most frequently cited as the most reliable indications that thickness problems were occurring in the casting area. Changes in
Figure 3.8. The fault tree diagram showing the potential causes for variations in thickness profile within the casting zone.
temperature were usually the first conditions most often checked by the engineers and operators when thickness variation or other casting related out-of-specification conditions existed.

**Statistical Tools for Examining Process Data**

- **Multivariate statistical tools for key process parameter selection**
  The second of the three parallel activities in the process optimization strategy was to examine historical data from the casting process areas. The goal of this work was threefold: to evaluate the relationships between the casting process signals and the polymer sheet casting related attributes, to identify key process variables, and to determine whether or not a predictive model could be developed using pre-existing qualitative product measures.

Multivariate statistical tools such as canonical discriminant analysis were used in this thesis for the historical data set evaluations. Multivariate statistical tools such as principal components analysis, canonical discriminant analysis, and partial least squares analysis are routinely and successfully employed to evaluate large populations of attribute data. Examples of these types of applications include instrument calibration, mixture analyses, and archeological classification of artifacts based on elemental composition. The theoretical basis of these techniques has been discussed previously (9-14) and is outside the scope of this thesis.

- **Historical process data examination**
  The first issue to resolve in examining historical data was to determine if the data was valid for model development. A total of thirty four types of casting signals were available from machine C representing temperature, pressure, and valve position signals. The process data had been archived in a process control system. Continuous, historical signals were collected for a three month time frame; May, June, and August 1992. The volume of casting data for a one week's period on a single machine was enormous; thirty four signals collected in ten minute intervals over a seven day period resulted in 34,272 data points. The data set for the three month period approximated 500,000 points. Upon visually examining the data, many I/O errors were found in the May and June data sets due to early problems
transferring data from the process controller to a personal computer. Data for specific times were deleted if one or more of the process signals were missing due to these I/O errors. In order to identify key casting process variables, the data sets had to be visually inspected to ensure that they contained valid process signals for all of the times examined.

Test data and occurrences of casting related machine waste conditions were identified using the operations reports and quality test results for May, June, and August. The process signals were categorized as "good" or "bad" based on operator comments during the runs, machine waste conditions, and product quality test results. The initial approach was to label data as "bad" if machine waste conditions such as wheel cleaning, turned edge or dirt problems occurred. The data was also labeled as "bad" when thickness variation tests were considered to be out of specification.

Quality test data were individually matched with the production schedule listings to match the tested rolls and identify operator comments particular to these rolls. No mechanism existed in the standard operating practices to perform this function.

After two iterations of data examination using several multivariate statistical techniques, data related to machine waste conditions were carefully scrutinized and deleted. It was not clear that the machine waste conditions were caused by or resulted in "bad" thickness conditions. Additionally, the data set was reworked to contain data that corresponded only to polymer rolls that had been uniquely tested for thickness. This step eliminated all process data for which no final product attribute data was available. The quality testing procedures for this work require that a single 35mm strip be analyzed from the end of an polymer roll every nine to twelve hours. No thickness tests were performed on the other rolls.

Over the three month period, a total of fifty two rolls were tested. Since the sheet samples taken for thickness testing in this study were obtained at the end of the roll, the data set was downselected to contain only the process signals within the 30-minute period at the end of the roll production. The process conditions resulting in "bad" thickness test results were broken
down into three categories as rated by the quality lab; A (action grade), P (passable limit), and N (nonpassable). An example of the data set is shown in Figure 3.9. The process conditions resulting in "good" thickness test results were labeled as G (good). Even though the resulting data set was much smaller (5500 data points), it was more indicative of the true casting process conditions at the time of actual product testing over the three month time period.

The statistical analyses were completed by J. P. Twist of the Chemometrics Laboratory using principal component analysis and canonical discriminant analysis. Initial assessment of this data set (Figure 3.10) showed three major groupings of data: one for the May - June time period, one for early August, and one for late August. The data labeled as G, A, P, and N could not be separated into independent clusters using these techniques. Examination of the downtimes and equipment maintenance work performed between the three time periods showed that major equipment changes and modifications to process set point values had occurred. These casting equipment and process set point changes were of sufficient magnitude to result in significantly different process conditions. The May, June, and August data were then chronologically grouped by time periods owing to the overriding affect of the different process conditions on the G, A, P, or N thickness categories.

- Prediction model for polymer sheet thickness quality

In the next round of analyses, data from each of the three time periods shown in Figure 3.10 were evaluated individually. The data in each of these time periods were successfully separated into clusters based on the thickness categories of G, A, P, and N using canonical discriminant analysis. The canonical discriminant analysis results are shown in Figure 3.11 for the May-June 1992 data. Separation of the four (G, A, P, and N) thickness categories can be easily observed in Figure 3.11 and represents a significant accomplishment in applying multivariate statistical tools to distinguish product quality test results by process conditions.

The canonical discriminant analysis results were similar for the other two time periods in that unambiguous separation of the process data based on
Figure 3.9. An example from a data set prepared for the multivariate statistical analysis.

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<th>Time</th>
<th>TV Assignment</th>
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<th>ProcessSig2</th>
<th>ProcessSig3</th>
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<td>12.768</td>
<td>54.976</td>
</tr>
<tr>
<td>27-08-92</td>
<td>07:40:00</td>
<td>AG</td>
<td>86.205</td>
<td>60.056</td>
<td>12.747</td>
<td>54.933</td>
</tr>
<tr>
<td>27-08-92</td>
<td>07:50:00</td>
<td>AG</td>
<td>86.249</td>
<td>60.168</td>
<td>12.792</td>
<td>54.974</td>
</tr>
<tr>
<td>29-08-92</td>
<td>03:50:00</td>
<td>Good</td>
<td>86.131</td>
<td>67.381</td>
<td>15.195</td>
<td>56.364</td>
</tr>
<tr>
<td>29-08-92</td>
<td>04:00:00</td>
<td>Good</td>
<td>86.119</td>
<td>67.386</td>
<td>15.207</td>
<td>56.251</td>
</tr>
<tr>
<td>29-08-92</td>
<td>04:10:00</td>
<td>Good</td>
<td>86.086</td>
<td>67.362</td>
<td>15.131</td>
<td>56.331</td>
</tr>
</tbody>
</table>
Figure 3.10. A plot of the 2 major principle component vectors showing the separation of data into 3 groups: 1) May-June 1992, 2) August 1-16, 1992, and 3) August 17-31, 1992.
Figure 3.11. A plot of the 2 major discriminant analysis vectors showing the separation of the G data from the A, N, and P data for the August 1 to 16, 1992 time period.
the four thickness categories was also achieved. A prediction model was
developed based on the ability of the model and the canonical discriminant
analysis to relate and separate qualitative thickness test results by casting
process signal values and conditions.

As a check on the canonical discriminant analysis results, the data sets
were tested and validated using the developed prediction models. The
prediction model for the May-June 1992 data was tested and is shown in
Figure 3.12. The prediction model was examined for its ability to predict
thickness quality as originally taken from the quality test results. As
shown in Figure 3.12, the prediction model correctly determined the A
thickness quality 98.89% of the time, the G thickness quality 100% of the
time, the N thickness quality 100% of the time, and the P thickness quality
100% of the time. Similar analyses were obtained for the two sets of August
1992 data.

Out of the thirty four casting process signals included in these data sets and
evaluated by the canonical discriminant analysis only nine casting process
signals were used in the prediction models. It is significant that only a few
process signals were key to establishing the casting process - product
relationship. This finding indicates that the model is valid. If all thirty
four process signals were required to create the prediction model, then it
would indicate that the model was trying to relate signal noise to product
test data and that the model was not valid.

The key casting process signals determined by the canonical discriminant
analysis are listed below:

- casting hopper water valve position
- casting valve pressure
- polymer filter pressure
- casting hopper temperature
- polymer stream temperature.

The casting hopper water valve position, the casting hopper water
temperature, and the polymer stream temperature play an important role
Figure 3.12. Comparison of the actual data with the results obtained from the prediction model.

**Generalized Squared Distance Function:**

\[
D_j^2(X) = (X - \bar{X}_j)' \text{COV}_{jj}^{-1} (X - \bar{X}_j)
\]

**Posterior Probability of Membership in Each GORB:**

\[
PR(j|X) = \exp(-0.5 D_j^2(X)) / \sum_{k} \exp(-0.5 D_k^2(X))
\]

**Number of Observations and Percents Classified into GORB:**

<table>
<thead>
<tr>
<th>GORB</th>
<th>AG</th>
<th>GOOD</th>
<th>NP</th>
<th>PL</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>AG</td>
<td>89</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td>98.89</td>
<td>0.00</td>
<td>1.11</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>GOOD</td>
<td>0</td>
<td>15</td>
<td>0</td>
<td>0</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>100.00</td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>NP</td>
<td>0</td>
<td>0</td>
<td>28</td>
<td>0</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>PL</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>45</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>TOTAL</td>
<td>89</td>
<td>15</td>
<td>29</td>
<td>45</td>
<td>178</td>
</tr>
<tr>
<td>PERCENT</td>
<td>50.00</td>
<td>8.43</td>
<td>16.29</td>
<td>25.28</td>
<td>100.00</td>
</tr>
<tr>
<td>PRIORS</td>
<td>0.2500</td>
<td>0.2500</td>
<td>0.2500</td>
<td>0.2500</td>
<td>0.2500</td>
</tr>
</tbody>
</table>

54
in maintaining the polymer temperature and the casting hopper temperature during casting. The casting valve pressure and the polymer filter pressure indicate the stability of the polymer viscosity, another critical parameter during casting.

It is crucial to note that polymer temperature, casting hopper temperature, casting valve pressure, and polymer filter pressure were the process signals cited by the engineers and operators as the first indications of thickness quality problems and other casting related problems. This is a significant step in changing the thinking of the process as an art into the process as a science based on multivariate statistical analysis.

Multivariate statistical techniques provide a unique way to view process-product relationships. Key casting parameters were identified with these techniques and the weighting or importance of the casting parameters on the thickness data were quantified. This activity was a first and important attempt at applying multivariate statistical techniques to qualitatively characterizing key process parameters to product attribute data. Even though a single predictive model could not be built for the sum total of the May, June, and August data sets due to significant and overriding process changes, a valid predictive model was developed for those times within each period when the process was unchanged. These models served to predict, based on process conditions, the resulting cast polymer sheet thickness profile quality.

- **Summary of three parallel activities**

A process optimization framework was developed to examine and characterize the relationship between the process conditions and the resulting product quality in conjunction with the FAB-PQ methods. This framework was applied to the casting process through three parallel thrusts of knowledge and experience, statistical process data, and theoretical calculations to determine the key casting parameters and their effect on polymer sheet metrics.

From the knowledge and experience activity, fault tree diagrams were completed for the casting process, documenting the relationships between
the casting process conditions and the resulting product attributes. These diagrams served to collect the opinions and knowledge of the operators and engineers in one document, highlighting areas for technical discussion, analysis, and experimentation.

A prediction model was developed as a part of the process data activity using multivariate statistical techniques to examine the relationships between casting signals and conditions and the polymer sheet thickness metrics. Historical casting process signals from a three-month timeframe were analyzed. The resulting prediction model demonstrated that casting process parameters could determine if the resulting cast sheet was within the quality bench specifications. Nine casting parameters out of a total of thirty four were found to be important to the casting of polymer sheet.

In examining the commonality between the parallel activities, it is important to note that the temperature and pressure signals cited by the operations personnel as key in indicating quality problems in the sheet profile comprised some of the nine casting parameters determined to be important by the multivariate statistical analyses.

The casting parameters selected from the parallel activities will be used in a designed screening experiment to determine the casting parameters and conditions critical to producing quality polymer sheet.
Chapter 4 Framework for Optimizing the Manufacturing Process, Part II: Screening Experiment and Product Attribute Metrics

**Designed Screening Experiment**

Based on the results of the data and information obtained through the three parallel activities presented in Chapter 3, a screening experiment was designed for the two FAB-PQ functions, distribute flow and shape catenary. It was hypothesized that the casting parameters selected from the results of these parallel activities would affect polymer sheet parameters directly or through interactions with one another. Due to the constraints of time and lost polymer sheet production, the screening experiment was limited to individual casting parameters and their main effect terms and did not include any interaction terms. Changes to production line conditions, such as polymer temperature, typically require as much as two to three hours to reach thermal equilibrium. As a result, there was insufficient production time available to run the number of experiments necessary to evaluate the interaction terms in a meaningful manner.

- **Screening experimental design and plan**

  The screening design chosen for this work was a systematic fractional replicate design developed by Cotter (15,16). This design is an economical experimental plan for investigating factors of which there is little prior knowledge and provides less ambiguous results than those provided by other designs (15). Screening experiments are preliminary experiments which isolate and rank the most important process parameters or factors from a larger number of factors affecting a product attribute and its measured response. Many screening experimental designs rely on strict assumptions about the nature of the interactions or their absence (15-18). These assumptions are often undesirable and can cause data interpretation problems. The systematic fractional replicate design was chosen because it incorporates the one-factor-at-a-time approach in which the main effects are varied one at a time. Additionally, and perhaps more importantly, this design does not require prior assumptions about interaction terms which results in a less ambiguous data interpretation.
For orthogonal fractional replicates, such as those used in factorial screening designs, the effects of a specific factor are aliased with unrelated factorial effects. With the systematic fractional replicate design employed here, the experimental results are much less ambiguous since the effects involving a specific factor are aliased together. This design also allows the estimation of the sum of all odd order effects involving a given factor as well as all even order effects involving a given factor.

For n factors the screening experimental matrix requires $2n + 2$ experiments. An example is shown below for $n = 3$ factors and $2n + 2 = 8$ experiments. This systematic fractional replicate design entails:

- one experiment with all factors low, (I)
- $n$ experiments with the factors changed to high on a one-at-a-time basis while all other factors are low, (II)
- $n$ experiments with the factors changed to low on a one-at-a-time basis while all other factors are high, (III)
- one experiment with all factors high, (IV).

The setup for the matrix design is shown below in Table 4.1:

<table>
<thead>
<tr>
<th>factor 1</th>
<th>factor 2</th>
<th>factor 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>II</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>III</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>IV</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

all low settings

block of low settings with each factor changed one at a time to high setting

block of high settings with each factor changed one at a time to low setting

all high settings
The calculations performed on the experimental data determine which of the n factors has an odd or even order effect on the cast polymer sheet metrics. The magnitude of the odd and even effects for each factor determine the rankings of the factors and the most important casting parameters.

**Experimental setup**
In this screening experiment, it was important to determine key casting parameters and conditions by quantifying their effect on cast polymer sheet attributes. The factors selected as screening experiment variables have been grouped into four categories; temperature, edge, catenary, and hopper atmosphere. These casting process parameters are listed below:

<table>
<thead>
<tr>
<th>Temperature</th>
<th>Edge</th>
</tr>
</thead>
<tbody>
<tr>
<td>polymer temperature</td>
<td>edge control temperature</td>
</tr>
<tr>
<td>hopper jacket temperature</td>
<td>edge control flow</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hopper Atmosphere</th>
<th>Catenary</th>
</tr>
</thead>
<tbody>
<tr>
<td>hopper atmosphere setting 1</td>
<td>vacuum under hopper</td>
</tr>
<tr>
<td>hopper atmosphere setting 2</td>
<td>height of hopper above wheel</td>
</tr>
<tr>
<td>hopper atmos. temperature</td>
<td>polymer pump speed</td>
</tr>
<tr>
<td></td>
<td>wheel speed</td>
</tr>
</tbody>
</table>

During the design of this experiment, it was anticipated that these eleven casting parameters would have main effects on the polymer sheet attributes of mean thickness, thickness profile, and edge shape. The expected main effects on the cast polymer sheet have been grouped into the same four categories shown above and are listed below:

<table>
<thead>
<tr>
<th>Temperature</th>
<th>Edge</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean thickness</td>
<td>edge profile</td>
</tr>
<tr>
<td>thickness profile</td>
<td>edge conditions (turned edge)</td>
</tr>
<tr>
<td>edge profile</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hopper Atmosphere</th>
<th>Catenary</th>
</tr>
</thead>
<tbody>
<tr>
<td>surface uniformity</td>
<td>surface uniformity</td>
</tr>
</tbody>
</table>
Changes in the polymer temperature and the hopper jacket temperature should cause changes in mean thickness, thickness profile, and edge profile. Changes in the edge control flow and temperature should affect edge profile and conditions such as turned edges. Changes in the hopper atmosphere setting 1, setting 2 and temperature should result in changes in surface uniformity and thickness profile. Changes in the vacuum under hopper, height of hopper above wheel, and the polymer pump and wheel speeds should cause changes in surface uniformity and longitudinal thickness profile.

The matrix for the casting screening experiment is shown in Figure 4.1 for ten factors. The eleventh factor, polymer pump speed, was omitted from the experiment because the factor is redundant with wheel speed. Polymer pump speed is set up to automatically follow wheel speed. Increasing or decreasing the polymer pump speed has the same effect on the thickness target value as decreasing or increasing the wheel speed. Twenty two experiments \((2n + 2)\) were planned. Twenty one experiments were run successfully. Polymer sheet samples were collected at the end of each experiment. Additionally, sheet samples were obtained for normal operating conditions at the beginning and end of the screening experiment. Experiment number 19 (roll number 12352) was not completed. The experimental conditions (all high settings) could not be sustained without causing the sheet to tear off and the machine to shut down.

All of the sheet samples were quantitatively analyzed for mean thickness, thickness profile, and edge profile. Qualitative surface uniformity measures were also made on these samples. Optical micrographs of the edges were obtained. Vibration measurements at the casting hopper were obtained during the experiment. Additional sheet samples were collected at normal operating conditions around the wheel circumference and in the longitudinal sheet direction and analyzed to determine the magnitude of thickness variation down the sheet and the around the wheel.
Figure 4.1. The design for the casting screening experiment.

<table>
<thead>
<tr>
<th>Experiment Number</th>
<th>Polymer Temperature</th>
<th>Casting Hopper Temperature</th>
<th>Edge Control Flow</th>
<th>Edge Control Temperature</th>
<th>Hopper Atmosphere Setting 1</th>
<th>Hopper Atmosphere Setting 2</th>
<th>Vacuum Under Hopper</th>
<th>Height Above Wheel</th>
<th>Wheel Speed</th>
<th>Roll Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>12331</td>
</tr>
<tr>
<td>1</td>
<td>+5 F</td>
<td>-5 F</td>
<td>-50%</td>
<td>-15 F</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Normal</td>
<td>Normal</td>
<td>12332</td>
</tr>
<tr>
<td>2</td>
<td>-5</td>
<td>-5</td>
<td>-50%</td>
<td>-15</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Normal</td>
<td>Normal</td>
<td>12333</td>
</tr>
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<td>+5</td>
<td>-50%</td>
<td>-15</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Normal</td>
<td>Normal</td>
<td>12334</td>
</tr>
<tr>
<td>4</td>
<td>-5</td>
<td>-5</td>
<td>50%</td>
<td>-15</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Normal</td>
<td>Normal</td>
<td>12335</td>
</tr>
<tr>
<td>5</td>
<td>-5</td>
<td>-5</td>
<td>-50%</td>
<td>+15</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Normal</td>
<td>Normal</td>
<td>12336</td>
</tr>
<tr>
<td>6</td>
<td>-5</td>
<td>-5</td>
<td>-50%</td>
<td>-15</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>Normal</td>
<td>Normal</td>
<td>12337</td>
</tr>
<tr>
<td>7</td>
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<td>-50%</td>
<td>-15</td>
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<td>8</td>
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<td>-50%</td>
<td>-15</td>
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<td>Low</td>
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<td>Normal</td>
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</tr>
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<td>-50%</td>
<td>-15</td>
<td>Low</td>
<td>Low</td>
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<td>Normal</td>
<td>Normal</td>
<td>12340</td>
</tr>
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<td>10</td>
<td>-5</td>
<td>-5</td>
<td>-50%</td>
<td>-15</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>+ 1/16&quot;</td>
<td>Low</td>
<td>12341</td>
</tr>
<tr>
<td>11</td>
<td>-5</td>
<td>+5</td>
<td>50%</td>
<td>+15</td>
<td>High</td>
<td>High</td>
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<td>Normal</td>
<td>Normal</td>
<td>12342</td>
</tr>
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<td>12</td>
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<td>-5</td>
<td>50%</td>
<td>+15</td>
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<td>High</td>
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<td>Normal</td>
<td>Normal</td>
<td>12343</td>
</tr>
<tr>
<td>13</td>
<td>+5</td>
<td>+5</td>
<td>-50%</td>
<td>+15</td>
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<td>High</td>
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<td>Normal</td>
<td>Normal</td>
<td>12344</td>
</tr>
<tr>
<td>14</td>
<td>+5</td>
<td>+5</td>
<td>50%</td>
<td>+15</td>
<td>High</td>
<td>High</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>12345</td>
</tr>
<tr>
<td>15</td>
<td>+5</td>
<td>+5</td>
<td>50%</td>
<td>+15</td>
<td>Low</td>
<td>High</td>
<td>Normal</td>
<td>High</td>
<td>Normal</td>
<td>12346</td>
</tr>
<tr>
<td>16</td>
<td>+5</td>
<td>+5</td>
<td>50%</td>
<td>+15</td>
<td>High</td>
<td>Low</td>
<td>Normal</td>
<td>High</td>
<td>Normal</td>
<td>12347</td>
</tr>
<tr>
<td>17</td>
<td>+5</td>
<td>+5</td>
<td>50%</td>
<td>+15</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>Normal</td>
<td>12348</td>
</tr>
<tr>
<td>18</td>
<td>+5</td>
<td>+5</td>
<td>50%</td>
<td>+15</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>+ 1/16&quot;</td>
<td>Normal</td>
<td>12349</td>
</tr>
<tr>
<td>19</td>
<td>+5</td>
<td>+5</td>
<td>50%</td>
<td>+15</td>
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<td>12350</td>
</tr>
<tr>
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<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>12351</td>
</tr>
<tr>
<td>21</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>12352</td>
</tr>
<tr>
<td>22</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>Normal</td>
<td>+5%</td>
</tr>
</tbody>
</table>
casting signals from the casting hopper were collected throughout the experiment. A summary of types of experimental analyses performed on the polymer sheet samples is shown below:

Quantitative and Qualitative Measurements on Collected Sheet Samples

<table>
<thead>
<tr>
<th>Thickness Profile</th>
<th>Surface Quality</th>
<th>Edge Profile</th>
<th>Vibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>circumference</td>
<td>qualitative</td>
<td>microscopy</td>
<td>at hopper</td>
</tr>
<tr>
<td>longitudinal</td>
<td></td>
<td>micrometer</td>
<td>vacuum</td>
</tr>
<tr>
<td>3 reps / experiment</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This chapter will present and discuss only the results of the mean thickness, thickness profile, and edge profile analyses.

Experimental Results and Discussion

- **Results of quality bench metrics for thickness profile**
  Widthwise polymer sheet samples were analyzed for mean thickness, thickness profile, and edge profile using a bench-mounted (quality bench) contact profilometer. Data points were acquired in increments of 0.04% of the sheet width along each 35 mm wide strip. A typical widthwise polymer sheet thickness data set contains approximately 2600 data points. Three widthwise polymer sheet samples were run and analyzed for each experiment number. Results of this data analysis determined whether or not the samples were within the specification limits for each of the following four categories:

  - mean or average thickness across the sheet
  - range of thickness values across the sheet
  - maximum thickness range in increments of 3% of the sheet across the sheet (max 3%)
  - maximum range in the first 35% of the sheet from both sheet edges (max 35%)

Results for the above thickness metrics for all of the experiments are plotted in Figures 4.2, 4.3, 4.4, and 4.5. Figure 4.2 shows the mean thickness value
Figure 4.2. Plot of the average thickness values for all of the experimental rolls.

acceptable thickness values for this experiment are 3.83 +/- 0.05 mils

Figure 4.3. Plot of the range values for all of the experimental rolls.

acceptable range is less than or equal to 0.2
**Figure 4.4.** Plot of the max 3% metric values for all of the experimental rolls.

acceptable values are less than or equal to 0.1

**Figure 4.5.** Plot of the max 35% metric values for all of the experimental rolls.

acceptable values are less than or equal to 0.06 mils
for each of the experiments by roll number. The thickness target for this experiment is 3.83 mils with upper and lower control limits of +/- 0.05 mils. The mean thickness value observed for each experiment was subtracted from this target value. All experiments except roll numbers 12341 (experiment 10) and 12354 (experiment 22) are within the acceptable mean thickness limit.

A high mean thickness value was obtained for roll number 12341 in which the height of the hopper above the wheel was raised by one sixteenth of an inch while all other factors were held low. The low mean thickness value obtained for roll 12354 was expected to be less than the 3.83 mil target. Normally, the polymer pump speed follows changes in the wheel speed to maintain a constant thickness at the wheel. In this experiment, the wheel speed was increased by five percent while the polymer pump speed was held constant, resulting in the observed lower thickness value.

Figure 4.3 shows the results of the range for each of the experiments. The upper and lower control limits require that the range be less than or equal to 0.2 mils. Only one roll number, 12346 (experiment 14), is within the acceptable range limit. For this roll number, 12346, the edge control temperature was low while the other factors were held high.

Figure 4.4 shows the results of the max 3% test. The upper and lower control limits require that this value be less than or equal to 0.1 mils. Again, only one roll number, 12346 (experiment 14), is within this acceptable limit.

Figure 4.5 shows the results of the max 35% test. The maximum value is given for each roll. The control limits require that this value be less than or equal to 0.06 mils. All rolls fall within the acceptable limit.

Examples of the thickness profile data are shown in Figure 4.6 for four experiments involving changes in the polymer temperature and the casting hopper temperature (roll numbers 12332, 12334, 12342, 12344).
Figure 4.6. Four thickness profiles from experimental conditions showing the effect of changing polymer and casting hopper temperatures.
Each trace is offset by 0.5 to separate the profiles for ease of viewing. It is important to note two things about experimental conditions for these profiles:

- the difference between the polymer temperature and the casting hopper temperature
- the parameter that has the higher temperature value (polymer or casting hopper).

Figure 4.6a and b show thickness profiles when the polymer temperature is larger than the casting hopper temperature by $9^\circ$F. These profiles represent roll numbers 12332 and 12342 and appear to have the largest edge to center difference of all of the profiles shown here. Figure 4.6c and d show thickness profiles when the polymer temperature is less than the casting hopper temperature by $9^\circ$F. These profiles are from roll numbers 12334 and 12344. Unlike Figure 4.6a and b, these thickness profiles in Figure 4.6c and d show little change from the center of the scan to the edge. All of the profiles have peaks or valleys present represent strut lines originating from the struts in the casting hopper. The presence of peaks or valleys depends upon whether the polymer temperature or the casting hopper temperature has the higher value. When the casting hopper temperature is higher, peaks occur in the thickness profile (Figure 4.6a). When the polymer temperature is higher, valleys occur in the thickness profile (Figure 4.6c).

- **Fourier analysis as a quantitative measurement tool**

It is crucial to be able to quantify differences in the experimental thickness profiles like those visually observed in Figure 4.6. The ability to quantify profile differences for specific process conditions would serve to strengthen the prediction model work (Chapter 3) which was based only on the four qualitative thickness categories of good, action grade, passable limit, and nonpassable. Fourier analysis provides additional quantitative information about the thickness profile features beyond the four quality bench thickness metrics previously presented. The periodogram program in Statgraphics Version 3.0 was used to perform these analyses.
Fast Fourier Transform (FFT) analysis was performed for each data set. Each data file contains approximately 2600 data points representing thickness data readings taken in 0.04% increments across the sheet sample. The Statgraphics program required that the data file size be limited to a power of two. The tenth power of two or 1024 points was chosen as the data file size. We made the assumption that the thickness profile was symmetrical about its center, which generally holds true for the polymer operating conditions as well as for the experimental results. Figure 4.7 shows the graphical area represented in the Fourier analysis versus the entire thickness profile. The Fourier analysis results were plotted as the square of the amplitudes of the resulting frequencies.

In order to illustrate the power of using Fourier transformation for quantifying thickness profile features, both the thickness profile and the Fourier analysis results for roll number 12353 (normal operating conditions) are shown in Figure 4.8a and b. The profile scan in Figure 4.8a visually shows the typical smile profile that is desired, having edges which are thicker than the center of the sheet. Quantitative data about the edges and their thickness or magnitude is obtained through Fourier analysis. The peak at 1 contains information about the magnitude of the edge profile. The peak at 0.067 shows the presence and magnitude of strut lines. For roll number 12353 in Figure 4.8b, the edge profile has a magnitude of 1.138 and the strut line peak has a small magnitude of 0.264.

Plots of the Fourier analysis results have been grouped by the four categories into temperature, catenary, hopper atmosphere, and edge and are shown in Figure 4.9, 4.10, 4.11, and 4.12. The legend for each figure refers the reader to the experimental roll numbers in Figure 4.1 for further information and data on the experimental conditions for these plots. The magnitudes of the edge profile and strut lines vary with experimental conditions. Some of the Fourier analysis plots show broadening and shoulder peaks at 0.2 and 0.13 inches. Note the differences in the magnitude of the Y axis for each of the four plots.
Figure 4.7. A representation of the data points analyzed in the periodogram. The Fourier transform used 1024 points from the thickness profile data set.
Figure 4.8a. Thickness profile for normal operating conditions of roll number 12353.

Figure 4.8b. Fourier analysis results of the roll 12353 thickness profile.
Figure 4.9. Fourier analysis results showing the effect of temperature category changes on the thickness profile attributes.
Figure 4.10. Fourier analysis results showing the effect of catenary category changes on the thickness profile attributes.
Figure 4.11. Fourier analysis results showing the effect of hopper atmosphere category changes on the thickness profile attributes.
Figure 4.12. Fourier analysis results showing the effect of edge category changes on the thickness profile attributes.
Comparison of quality bench metrics and Fourier metrics

In the thickness profile plots of Figure 4.6 we observed visible differences and similarities between the four thickness profiles of roll numbers 12332, 12334, 12342, and 12344. The Fourier analyses of these profiles are shown in Figure 4.9 a, b, c, and d, respectively for the temperature category conditions. The quality bench thickness metrics are listed below in Table 4.2 for these four profiles along with the Fourier analysis data for the edge profile peak at 1 and the strut line peak at 0.067. Fourier analysis provides quantitative data and complimentary information about the thickness profile shapes and differences between experimental settings. Metrics for the normal operating conditions of roll 12353 are included for contrast.

<table>
<thead>
<tr>
<th>Table 4.2. Test results.*</th>
<th>Quality Bench metrics</th>
<th>Fourier peaks</th>
</tr>
</thead>
<tbody>
<tr>
<td>roll #</td>
<td>experiment conditions</td>
<td>mean</td>
</tr>
<tr>
<td>12332</td>
<td>pt(+),ht(-),all others(-)</td>
<td>3.849</td>
</tr>
<tr>
<td>12344</td>
<td>pt(+),ht(-),all others(+)</td>
<td>3.843</td>
</tr>
<tr>
<td>12334</td>
<td>pt(-),ht(+),all others(-)</td>
<td>3.830</td>
</tr>
<tr>
<td>12342</td>
<td>pt(-),ht(+),all others(+)</td>
<td>3.807</td>
</tr>
<tr>
<td>12353</td>
<td>normal operation</td>
<td>3.836</td>
</tr>
</tbody>
</table>

*pt is polymer temperature, ht is hopper jacket temperature; + is high setting, - is low setting.

There is little change in three of the quality bench metrics, mean, max 3%, max 35%, in contrast to the experimental changes in the polymer and casting hopper temperature. The fourth quality bench metric, range, shows a small change in value for roll number 12334.

The Fourier analysis results for the peak at 1 and peak at 0.067 are smallest in magnitude when the polymer temperature is high (+) and the hopper jacket temperature is low (-) as shown in rolls 12332 and 12344. The Fourier results for the peak at 1 and peak at 0.067 are largest in magnitude when the polymer temperature is low (-) and the casting hopper temperature is high (+) as shown in rolls 12334 and 12342. As evident from the Fourier analysis values listed above, the experimental conditions for the polymer
temperature and hopper temperature (high or low) play a significant role in determining edge profile and the presence or absence of strut lines.

Additionally, whether or not the other experimental signals were held high or low had a smaller effect on the edge profile and strut line characteristics. Examining the Fourier analysis results for rolls 12334 and 12342 in which the experimental signals were all either high or low while the polymer and hopper temperature conditions were the same, shows higher Fourier values when the remaining signals are low as opposed to when the remaining signals are high. This implies that there may be cumulative single and higher order effects from the other experimental conditions but that they are not as high in magnitude as the polymer temperature and casting hopper temperature conditions. Working up the screening experiment data will serve to verify this.

Figure 4.13 shows a comparison of the Fourier metric at a peak of 1 to the quality bench metrics. The comparison is dramatic. The Fourier metric has a much larger dynamic range of response across the experimental roll numbers in contrast to the small changes in response with the quality benchmark metrics. A larger dynamic range achieved with the Fourier metric provides improvements in signal to noise ratio and the ability to mathematically assess the differences between experimental condition settings.

As we can see through this evaluation, Fourier analysis yields a convenient means to quantify the similarities and differences in these thickness profiles expanding beyond and providing complimentary information to the current quality benchmark thickness metrics.

- Data analysis for the screening experimental matrix
After the analyses on the polymer sheet samples were completed, the experimental design calculations were performed to determine whether or not each of the ten factors had an odd or even order effect on the cast polymer sheet metrics. The following calculations were performed to
Figure 4.13. Plot comparing the Fourier metric peak of 1 to the four quality bench metrics.
determine the odd effect ($C_{odd}$), the even effect ($C_{even}$), and the magnitude of the effect ($M$):

\[
C_{odd,n} = \frac{1}{4} \left[ (Y(IV) - Y(III,n)) - (Y(I) - Y(II,n)) \right]
\]

\[
C_{even,n} = \frac{1}{4} \left[ (Y(IV) - Y(III,n)) + (Y(I) - Y(II,n)) \right]
\]

\[
M_n = |C_{odd,n}| + |C_{even,n}|
\]

The parameter $Y(IV)$ is the value of the product metric for the experiment with all factors high. The parameter $Y(I)$ is the product value for the experiment with all factors low. The parameter $Y(III),n$ is the value for the $n$th factor where $n = 1$ to $n$ with the $n$th factor held low and all other factors held high. For example with $n = 1$, the polymer temperature is low and all other factors are high. Conversely, the parameter $Y(II),n$ is the value of the product metric for the $n$th factor where $n = 1$ to $n$ with the $n$th factor held high and all other factors held low. In this case, the polymer temperature is high and all other factors are low.

For this data analysis, polymer sheet metrics obtained for the 12333 roll number represent the all low settings and are the values for the $Y(I)$ parameter in the $C_{odd}$ and $C_{even}$ equations listed above. Polymer sheet metrics obtained for the 12351 roll number represent the all high settings and are the values for the $Y(IV)$ parameter. As pointed out earlier, the experiment that was to be the all high settings, experiment number 19 (roll number 12352), was not completed because the experimental conditions could not be sustained without causing the sheet to tear off and the machine to shut down. The 12351 roll number was chosen as a substitute for the all high setting conditions of $Y(IV)$. This assumption is made knowing that some error will be imparted on the analysis results. The author, based on a careful and critical examination of all of the casting work and discussions with the polymer engineers, believes that roll 12351 is the best choice for $Y(IV)$. This is, after all, a screening experiment in which we are concerned with selecting the top four or five casting parameters having the largest effect on the polymer sheet thickness metrics. A more in-depth
experiment follows a screening experiment, focusing on these four or five key casting parameters and quantifying the magnitudes of their main effects and interactions.

An example of the calculations is shown below for the polymer temperature factor and the Fourier analysis peak at 1.

\[
C_{odd} = \frac{1}{4} \left[ (0.395 - 1.971) - (1.874 - 0.009) \right] = -0.86
\]

\[
C_{even} = \frac{1}{4} \left[ (0.395 - 1.971) + (1.874 - 0.009) \right] = 0.07
\]

\[
M_{polymer\text{-}temp} = | -0.86 | + | 0.07 | = 0.93
\]

Calculations were performed for two Fourier analysis peaks at 1.00 and 0.067 and four quality bench metrics. The complete data set and results are listed in the Appendix. Bar charts of the magnitude values for each casting parameter are shown for the six metrics in Figures 4.14, 4.15, 4.16, 4.17, 4.18, and 4.19. Table 4.3 lists the ranking order for the casting parameters for each metric.

<table>
<thead>
<tr>
<th>Table 4.3. Rankings of the Fourier and quality bench metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Metric</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>polymer temperature</td>
</tr>
<tr>
<td>hopper temperature</td>
</tr>
<tr>
<td>edge control flow</td>
</tr>
<tr>
<td>edge temperature</td>
</tr>
<tr>
<td>atmosphere setting1</td>
</tr>
<tr>
<td>atmosphere setting2</td>
</tr>
<tr>
<td>atmos. temperature</td>
</tr>
<tr>
<td>vacuum under hopper</td>
</tr>
</tbody>
</table>

* Rankings listed from 1 to 5 with 1 having the largest magnitude value.

- **Examination of the screening experiment results**
For the Fourier analysis peak at 1, the polymer temperature and the casting hopper temperature show the largest effect on the edge profile.
Figure 4.14. Bar chart showing the casting parameter magnitudes calculated for the Fourier metric at peak of 1.

Figure 4.15. Bar chart showing the casting parameter magnitudes calculated for the Fourier metric at peak of 0.067.
Figure 4.16. Bar chart showing the casting parameter magnitudes calculated for the average thickness metric.

Figure 4.17. Bar chart showing the casting parameter magnitudes calculated for the range metric.
Figure 4.18. Bar chart showing the casting parameter magnitudes calculated for the max 3% metric.

Figure 4.19. Bar chart showing the casting parameter magnitudes calculated for the max 35% metric.
magnitudes of 0.933 and 0.840 respectively. Because of the similarities in magnitude, the polymer temperature and the casting hopper temperature both play an important role in determining edge profile conditions. The hopper atmosphere setting 1, vacuum under hopper setting, and the edge control temperature show the next largest effects at 0.495, 0.480, and 0.386 respectively.

For the Fourier analysis peak at 0.067, the casting hopper temperature and the polymer temperature again show the largest effect on the presence and magnitude of strut lines with magnitudes of 0.220 and 0.061 respectively. The casting hopper temperature appears to have a stronger effect on the strut lines than the polymer temperature. The edge control flow and edge control temperature show the next largest effects at 0.47 and 0.40 respectively.

For thickness target, polymer temperature, edge control flow, hopper atmosphere temperature, casting hopper temperature, and hopper atmosphere setting 1 round out the top five effects with magnitudes of 0.012, 0.010, 0.007, 0.006, and 0.006 respectively.

For the range, polymer temperature, vacuum under hopper setting, casting hopper temperature, edge control flow, and edge control temperature are the top factors with magnitudes of 0.081, 0.049, 0.38, 0.027, and 0.020 respectively.

For the max 3%, the casting hopper temperature, vacuum under hopper setting, edge control temperature, edge control flow, and hopper atmosphere setting 1 are the five main factors with magnitudes of 0.025, 0.013, 0.012, 0.009 and 0.009 respectively.

For the fourth quality bench metric, the max 35%, the hopper atmosphere temperature, polymer temperature, and hopper atmosphere setting 2 are the top three factors with four other parameters tied for the fourth main effect. The magnitudes of the top three factors are 0.013, 0.009, and 0.006 respectively.
Less consistent results were found when examining the quality bench metrics in contrast to the Fourier metrics. The quality bench metrics provide little insight as to which experimental signals most affect the thickness profile. For example, the mean thickness values with a target thickness specification of 3.83 +/- 0.05 mils changed very little throughout the experiment. The mean thickness values ranged from 3.807 to 3.885 across all of the roll numbers. Range showed the largest amount of variation with values from 0.197 to 0.456. Additionally, the range values appeared to be larger for the first ten experiments than for the last ten experiments. The values for the max 3% metric varied randomly throughout the experiment with only small differences observed among the experiments from 0.092 to 0.165. The values for the max 35% metric were even smaller for the experimental rolls, ranging randomly in values from 0.000 to 0.046. It would be difficult to prove that the changes observed in this last metric were not just variations in background noise.

It is important to note from the Cotter matrix calculations that the magnitudes for the Fourier metrics are one to two orders greater in magnitude than those for the quality bench metrics. The order of magnitude difference is more significant (up to three orders) when comparing the magnitudes of the Fourier metrics to the mean thickness, max 3% metric, and max 35% metric.

The larger dynamic range obtained with the Fourier metrics provides a larger signal to noise ratio and makes it easier to relate and quantify the change in in Fourier metric magnitudes with changes in experimental conditions. It is questionable as to whether the small differences in the quality bench metrics are valid for assessing the differences in our experiment conditions and selecting key parameters.

As a final step in the analysis, we wanted to determine whether or not there was any correlation between the Fourier metrics and the quality bench metrics. Regression analyses were performed on these metrics to see if any relationships existed. The results are summarized in Table 4.4.
Table 4.4. Regression of Fourier metrics & quality bench metrics

<table>
<thead>
<tr>
<th>Regression X and Y</th>
<th>Regression coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak 1 vs mean</td>
<td>0.148</td>
</tr>
<tr>
<td></td>
<td>0.860</td>
</tr>
<tr>
<td>vs range</td>
<td>0.117</td>
</tr>
<tr>
<td>vs max 3%</td>
<td>0.565</td>
</tr>
<tr>
<td>vs max 35%</td>
<td></td>
</tr>
<tr>
<td>Peak 0.067 vs range</td>
<td>0.237</td>
</tr>
<tr>
<td></td>
<td>0.561</td>
</tr>
<tr>
<td>vs max 3%</td>
<td>0.346</td>
</tr>
</tbody>
</table>

The only correlation of interest was between the Fourier metric at peak of 1 and the quality bench range metric ($R = 0.860$). A correlation value of 0.9 or larger is desired. All other regression results were 0.565 or less and were considered insignificant.

**Examining variability in the polymer sheet thickness**

Testing practices used in this thesis work for thickness quality require that a single widthwise strip be analyzed every nine to twelve hours apart for each of the polymer machines. The single sheet sample is cut from the end of the roll. The profilometer analysis is the only measure of the machine cast thickness profile during that nine to twelve hour time period. Four quality bench metrics, mean or average thickness across the sheet, range, max 3%, and max 35%, are determined on the profilometer data. Judgements on these criteria are made by quality laboratory operators who perform the test on the 35 mm widthwise strip sample and evaluate the resulting strip chart recording of the thickness profile plot. Thickness profile variations often occur among strips adjacent to one another (ie., downweb) which are sufficient enough to make analysis difficult.

- **In-depth evaluation of thickness variation**

It is critical to determine the nature and the magnitude of thickness variation across and down the polymer sheet so that these variations can be characterized and a statistically appropriate number of widthwise strips

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analyzed to get the true thickness profile. Two approaches were undertaken to better assess the thickness variation in the polymer sheet under normal and steady state operating conditions as shown in Figure 4.20a & b:

- examination of thickness variation around the casting wheel circumference
- examination of thickness variation in the longitudinal direction over three wheel circumference lengths

It was important to determine the natural thickness variation around the wheel due to ovality or out-of-roundness in the wheel dimensionality. A 100 foot polymer sheet sample was obtained during the normal, steady state operating conditions of roll number 12353. The 100 foot sheet was marked at each spoke position on the wheel. A widthwise sheet strip was cut at each spoke marking and also at the point halfway between the spoke positions for widthwise thickness testing. Sixteen strips covering the entire wheel circumference were prepared and analyzed using the lab profilometer. To remove noise in the profilometer digitized points, an eight nearest neighbor smoothing operation was performed.

A plot of the three-dimensional profile is shown in Figure 4.21. The plot shows the thickness variation from the target value across the width of the sheet in 0.04% increments and down the length of the sheet in five foot increments. The smoothed data points are within specification for the product type. The allowed variation in thickness for this experiment was +/- 0.05 mils. Even though some variation can be observed in this 3-D plot, it is significant to note that the variation around the machine C wheel is within the allowed specification range. The three-dimensional wheel circumference plot shows us, for widthwise samples spaced a half spoke distance apart (low frequency scale), that the natural variation occurring from any wheel out-of-roundness is not significant.

Longitudinal sheet testing was performed to examine any thickness variations that might occur on a smaller scale or at a higher frequency than discernable with the wheel circumference sampling scheme.
Figure 4.20. The sampling scheme for evaluation of the thickness variation: a) around the wheel circumference and b) in the longitudinal direction.

widthwise samples taken:
- at each wheel spoke numbered 1 through 8
- at location halfway between each spoke

continuous, longitudinal samples taken:
- at the left edge of the sheet
- at the center of the sheet
- at the right edge of the sheet
Figure 4.21. A 3-dimensional plot of the thickness variation occurring around the wheel circumference.
Additionally, it was important to examine any differences in thickness variations occurring in the left side, the right side, and the center of the sheet.

A continuous sheet sample was obtained during the normal operating conditions of roll number 12353. Continuous samples were cut at the left (approximately three inches in from the edge), the right, and the center of this sheet. These samples are continuous longitudinal sheet strips as opposed to widthwise strips. Each longitudinal sample was digitized on the profilometer to obtain the data files. The data files were analyzed using a Fourier analysis program on MatLab software.

The Fourier analysis plots are shown in Figure 4.22 and 4.23 for the right and center continuous samples. Figures 4.22a and b represent the thickness variations obtained for the right sheet sample. The Fourier analysis is nondescript and shows no high frequency components. Of interest is the peak at 0.125 of small magnitude, 0.009, representing the wheel spoke distance.

Figure 4.23 represents the center sheet sample. The Fourier analysis also shows few features and no high frequency components. A peak is also observed at 0.125 of small magnitude, 0.018. All of the variation measured in the longitudinal sheet samples is within the allowable specification. The Fourier analysis for the left sheet sample was omitted because there were no new or different findings.

The results and findings from the wheel circumference and longitudinal testings are significant since they verify that variation around the wheel is within the allowable specification range for both high frequency and low frequency components.
Figure 4.22. A plot of the longitudinal thickness variation in a continuous sample obtained from the right side of the sheet.
Figure 4.23. A plot of the longitudinal thickness variation in a continuous sample obtained from the center of the sheet.
Recommendations

The following recommendations, based on the Chapter 4 results, are:
- a designed experiment should be conducted focusing on the major factors or casting parameters determined by the screening experiment. These parameters are:
  - polymer temperature
  - casting hopper temperature
  - edge control flow
  - hopper atmosphere setting 1.

A designed experiment on the casting hopper with these four parameters will help to determine optimal settings for cast sheet thickness profile.

- Fourier analysis should be implemented as a quantitative measurement tool for thickness profile testing. Fourier analysis software packages are readily available and can be easily incorporated into the existing quality bench computer-based profilometer system. This tool can be made transparent to the quality bench operator so that understanding Fourier analysis will not be required to interpret the data. The Fourier technique provides an improvement over current measures by:
  - characterizing edge profile information
  - increasing dynamic response range for improved edge profile analysis
  - increasing the signal to noise ratio.

Current metrics have been demonstrated to have little value in measuring changes that have been deemed necessary to improve the casting operation as shown through the casting experiment

- The Fourier analysis tool must be used to determine what the ideal thickness profile should be. First of all, the desired edge profile should be determined and quantified with the Fourier metrics. Specifications must be developed for the desired quality polymer sheet profile. A new set of metrics can then be implemented for normal production testing use.
Chapter 5 Improving the Manufacturing Operations

Highlights and Accomplishments
The objective of this thesis was to develop and demonstrate a systematic approach promoting consistency of operation across the polymer manufacturing process while increasing quality throughput in a cost effective manner. This framework was comprised of two parts: the asset utilization model and the process optimization framework. The asset utilization model, described in Chapter 2, served as a tool for examining how effectively and efficiently the manufacturing equipment is being operated.

The asset utilization calculations served as common metrics across a number of polymer machines. Increased quality throughput, can be achieved by driving improvements through the asset utilization manufacturing productivity parameter numbers without capital investment in additional machines. The asset utilization model acts as a platform to set direction and focus for continuous improvement activities on the low asset utilization machines. Internal and external benchmarking activities can be undertaken to establish world-class practices and implement these best practices within a manufacturing operations. Furthermore, the asset utilization model and parameter numerics can help to link continuous improvement efforts and the cost-benefit tradeoffs of these improvement programs to accomplishing five year business unit goals and objectives.

The process optimization framework presented in Chapters 3 and 4 provided a holistic method for examining and quantifying process-product relationships as a part of the function-based process quality methods. This framework was specifically applied to a casting process in this thesis scope. The casting process conditions and operating practices were evaluated and related to the cast polymer sheet thickness profile. Three parallel activities, knowledge and experience, statistical process data, and theoretical calculations, were undertaken to determine casting parameters which were critical in creating the cast polymer sheet thickness profile attributes.
As a part of the knowledge and experience thrust, fault tree diagrams were completed in detail for the casting and coating areas, documenting the relationships between the casting and coating process conditions and resulting product attributes. Importantly, these diagrams served as vehicles for gathering and recording the opinion and knowledge of the operators and engineers in one document, helping to highlight specific areas for technical discussion, development work, and experimentation. Additionally, the diagrams can be used to facilitate problem solving discussions about specific machine areas and help in developing CAGs (corrective action guidelines) for problem resolution. As a part of this thesis work, the casting fault tree diagram was used to examine the process conditions in the casting area causing product waste.

A prediction model was developed as a part of the process data thrust in which multivariate statistical techniques were employed to examined the relationship between the casting process and cast sheet attributes. This model demonstrated its ability to determine whether or not quality product was made from process conditions. Nine casting process parameters out of thirty four were found to be critical to the casting of polymer sheet. It should be feasible, with additional work, to develop a prediction model that can be used in real time to determine whether or not at the moment of casting that a polymer sheet will be within specification. This model will provide information on a real time basis allowing for correction of the process and will help the polymer operations achieve consistency in the casting process. The model will serve as the mechanism for verifying that the casting process and the two FAB-PQ functions of distribute flow and shape catenary are producing product that is within specification.

The third activity conducted in parallel examined theoretical considerations of the casting process to determine the magnitude of change anticipated on the casting conditions. This work served to validate the findings of the first two thrusts.

The parallel activities lead to a screening experiment which confirmed four critical casting parameters for polymer sheet casting. Additionally, Fourier analysis provided a new and complimentary measurement tool to
quantify the edge profile and should lead to improvements in the way that the thickness profile is assessed and evaluated for quality and desired sheet production.

This holistic process optimization framework can be readily transferred to the other polymer machines and can serve as a proactive method for waste reduction across the polymer operations.

**Capacity Gained through the Asset Utilization Model**

The asset utilization model and four manufacturing productivity parameters therein act as drivers for gaining extra capacity and reducing operational costs with existing equipment by improving the overall efficiencies of equipment utilization. For example, let's examine just one of the four manufacturing productivity parameters, the yield parameter, for the polymer machines studied in Chapter 2. The yield values for the eight polymer machines are listed in Table 5.1 for the January through September 1992 time period. These normalized values range from 0.75 to 1 across the machines studied. There are three machines with normalized yield values less that 0.89, two machines between 0.89 to 0.94, and three machines over 0.94. If the normalized yield values of the low efficiency machines for this group of eight machines could be improved to yields of 0.94 or greater, the additional yield achieved would be equivalent to a capacity gain for these eight machines of nearly 7.5%. Similarly, making improvements to yields of 0.94 or greater on all low efficiency machines across the operation would result in a capacity gain of nearly 8%.

Additional polymer sheet capacity gain of 8% provides two opportunities for the polymer operations. First, if this manufacturing process is the bottleneck operation, they can accomplish a capacity increase without having to spend capital money to build additional capacity. Second, if there is no need for additional capacity, they can reduce the overall number of machines by nearly 8%, providing an opportunity to reduce operations and labor costs.

Accomplishing a normalized yield goal of 0.94 across the polymer machines should not be difficult to attain. Looking again at Table 5.1, there
Table 5.1. Potential capacity gain by yield improvements to 0.94.

<table>
<thead>
<tr>
<th>Machine</th>
<th>Current Yield %</th>
<th>Yield Improvements</th>
<th>Increased quality hours ratio</th>
<th>Capacity gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.75</td>
<td>0.94</td>
<td>1.25</td>
<td>25.20</td>
</tr>
<tr>
<td>D</td>
<td>0.97</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
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<td>1.21</td>
<td>21.18</td>
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<tr>
<td>G</td>
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<td>0.94</td>
<td>1.02</td>
<td>1.98</td>
</tr>
<tr>
<td>H</td>
<td>0.87</td>
<td>0.94</td>
<td>1.08</td>
<td>8.43</td>
</tr>
<tr>
<td>I</td>
<td>0.90</td>
<td>0.94</td>
<td>1.04</td>
<td>4.42</td>
</tr>
<tr>
<td>M</td>
<td>1.00</td>
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<tr>
<td>O</td>
<td>0.99</td>
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</tbody>
</table>

Total gain for 8 machines, % 7.5

Increased capacity for these eight machines from yield improvements to 0.94 is approximately 7.5%.

Increased capacity across the operations from yield improvements to 0.94 is approximately 8%.
are two machines within the 0.89 to 0.94 range. Little effort would be required to increase the yields on these machines to 0.94. Thus, the three machines with normalized yield values of less than 0.89 should be the focus of the polymer operations' continuous improvement activities. These machines would benefit from the process optimization framework described in Chapter 3 and the function-based process quality methods under development for machine C in order to achieve and maintain these yield improvements. Similar improvements in machine efficiencies and capacity gains could be worked out for the other three manufacturing productivity parameters.

**Application of the Asset Utilization Model to other Manufacturing Processes**

The asset utilization model and manufacturing productivity parameters were tools which facilitated systematic comparisons of equipment efficiencies across the polymer machines within the continuous casting manufacturing operation. These tools can be easily adaptable across different manufacturing operations which are set up as batch or job shop operations. As one might expect, batch or job shop operations would typically have lower run time efficiency numbers than a continuous operation because of the setup time and product change times required for each batch or piece to be produced. Each operation would have to be individually assessed to determine the manufacturing productivity parameter of most significance for focusing the continuous improvement efforts in order to attain machine efficiency increases and capacity gains.

The asset utilization model is widely applicable to a variety of different types of manufacturing technologies such as polymer sheet manufacturing, paper manufacturing, metal rolling operations, forging operations, semiconductor fabrication operations, and other industries. This model and calculations has been successfully applied to operations as diverse as the continuous polymer sheet manufacturing process, batch aluminum rolling and finishing operations, job shop forging parts production, and bauxite mining operations (1-3).
Application of Process Optimization Framework across the Polymer Manufacturing Operation

As shown above, increasing the normalized yield numbers across the polymer machines to 0.94 would result in a capacity gain of nearly 8%. The holistic process optimization framework and function-based process quality methodologies are the systematic process improvement tools needed to accomplish this capacity gain by reducing the process variability and product waste. In getting started on waste reduction efforts and insuring that the process improvement work is leveraged, the operational similarities and differences across the polymer machines must be assessed and documented. Determining these machine-to-machine similarities and differences is essential to implementing a valid and efficient improvement strategy in terms of manpower, time, and cost. It is especially critical that this approach be undertaken among those machines manufacturing the same type of product.

The process optimization framework developed as a part of this thesis project was applied to the casting process since it was determined that the casting area accounts for approximately 60% of the polymer waste. In this work, the casting process conditions and operating practices were evaluated and related to the cast polymer sheet thickness profile conditions for machine C. A significant step in reaching the goal of increasing the yield on the other low yield machines would be to determine how this framework and prediction model on the machine C casting process could be implemented on the low yield machines to reduce casting waste. The machine-to-machine similarities and differences documented as described above would facilitate this transfer and implementation and ensure that the yield goal was attained across the polymer machines.

Application of Process Optimization Framework to other Manufacturing Processes

The process optimization framework was developed as a part of the function-based process quality method. As previously highlighted in Chapters 3 and 4, these systematic approaches incorporate the unique features of functional flow analysis and verification strategies for characterizing a manufacturing process and reducing process variability.
These unique features make these approaches distinguishable and more broadly encompassing in scope than other process optimization approaches previously studied or documented in the literature. Numerous process optimization strategies in use in manufacturing operations today and cited in research journals typically lack the functional flow analysis and the verification strategy tools and include only the process control and optimization steps.

The process optimization framework and function-based process quality method are being applied to the polymer manufacturing operation. The function-based process quality technique has been applied to polymer processing, paper manufacturing, and other operations (5-8). These methods are systematic tools for examining and reducing process and product variability and can be implemented on any manufacturing process. Chemical processes, such as those chosen for application in this thesis, are but one example of where a need exists for maintaining an invariant and robust process.

**Four Manufacturing Laws and their Relevance to Polymer Operations**

Four manufacturing laws evolved from this work and are discussed as follows:

- **Metrics must be clean, true, and easily understandable.** Each of the asset utilization model manufacturing productivity parameters are calculated on an independent and individual basis. The yield parameter measures only the amount of time spent producing quality product. The run time efficiency parameter determines only the effect of set up time and frequency of product changes on the production cycle time. The availability parameter assesses only the effect of downtime, maintenance, and idle time on the amount of time the equipment is available to run product. The run speed efficiency parameter compares only the operating speed with the maximum allowed equipment speed. Since these parameters focus on specific and independent areas of equipment utilization, continuous improvement efforts can be easily pinpointed and defined for each parameter. Additionally, it is clear what must be changed and improved in order to obtain increases in each of these four manufacturing productivity parameter numbers.
In Chapter 2, the Company reliability parameter was compared to the asset utilization model yield parameter. This comparison showed that even though similar numbers were determined by the two parameters for the January through September 1992 time period, the ways in which the values obtained for two parameters were calculated were quite different. As stated above, the asset utilization model yield calculation calculates the percent of the run time that the machine manufactures quality product. The run time is determined in the availability calculation and is based on subtracting the scheduled downtime, unscheduled maintenance, and the idle time from the calendar time. This metric is a clean and independent metric of quality product produced during machine run time.

The Company reliability parameter is not an independent parameter and does not independently measure the percent of run time that quality product is made but instead measures the percent of time quality product is made as determined by scheduled downtimes and charge hours. These two times, scheduled downtime and charge hours are subtracted from the calendar time. This reliability metric confounds several variables and precludes an unbiased calculation of available hours for running the machine.

- **Performance incentives that encourage modification of the performance metrics must be prohibited.** The value of a model such as the asset utilization model is in obtaining a baseline which is a real and valid indication of the state of efficiency regarding equipment utilization. If done correctly using the definitions of the manufacturing productivity parameter calculations presented in Chapter 2, Table 2.2, the asset utilization model numbers can only increase and improve with continuous improvement efforts to increase efficient equipment utilization.

Manufacturing productivity parameters which are modified to take out or "correct" any part of the calculation result in numbers which are not a true representation of the state of equipment utilization. Progress might be attainable through continuous improvement activities, but plateaus will be reached and then the productivity parameters will need to be redefined and
recalculated with the asset utilization numbers getting worse at various points in time as a result of these redefinitions.

For example, a major issue which arose in reviewing the asset utilization results was the definition of the run speed efficiency parameter and the way in which the maximum operating speed was determined. Originally, for this parameter, the speed limitations of process equipment were used for the type 1 machine calculations and the speed limitations based on allowable product characteristics were used for the type 2 machine calculations to determine the maximum achievable operating speeds. There was considerable discussion and concern expressed from the polymer operations that these speed limitations did not correctly represent the production situation. The largest concern was for the type 2 machines. The thicker the polymer sheet produced on these machines the slower its actual production speed. The production speeds for these products were based on product characteristics.

The polymer operations wanted to use the speed limitations of manufacturing these products as the maximum operating speeds in the run speed efficiency parameter calculations. The speeds for these type 2 machines were, in many cases, lower than the maximum operating speed possible on these machines. While debates and discussions such as this one will frequently take place in setting up metrics and how they are defined, modifying the definitions to perceived reality only penalizes the operation in the long run.

For example, if the maximum operating speed for a machine is chosen based on speed limitations based on product type and improvements are made in run speed efficiency on that machine, then, the run speed efficiency numbers will eventually exceed 100%. The maximum operating speed will then need to be reset and a new product limited speed value selected. The operation will have to account for this change observed in the run speed efficiency parameter and the overall asset utilization number as an increase to 100% and a drop back to a lower percentage when the product limited speed value is increased. It is better to use the actual speed
limitation of the process equipment as the baseline value for run speed efficiency when the asset utilization model is set up.

- **Single measures of product are not sufficient to properly quantify the product quality.** Sampling practices used in this thesis work for thickness profile required that a single sheet sample be taken every nine to twelve hours to determine the quality of the polymer sheet thickness profile. If a sample was found to be within specification, the rolls in that nine to twelve hour time period were considered to be within specification. If a sample is deemed as out of specification, another sample was taken, and, if the second sample was determined to be within specification, the rolls in the nine to twelve hour period were also considered to be within specification. If the second sample was determined to be out of specification, then each roll produced in the nine to twelve hour period was sampled to determine whether or not the roll was within specification.

The concern is that a single 35 mm widthwise sheet sample and thickness profile test results determine whether or not an entire roll is within specification. Sometimes, variation around the casting wheel itself is sufficient to result in producing two samples in which are significantly different. The minimum number of samples needed to properly quantify product quality and the thickness profile must be determined. Additionally, sampling on a more frequent basis should be implemented.

- **Multivariate statistical techniques provide insight into the state of the process, serving to predict product quality.** As presented in Chapters 3 and 4, a data set from a three month period of the casting process signals and qualitative thickness profile values were examined using multivariate statistical techniques. In an early stage of examination, the results of the multivariate statistical analysis showed separation of the data into three clusters based on changes that had been made to the casting process signal set points and to parts of the casting equipment during downtimes. An important message from these results in that the effect of changing equipment and process signal set points must be characterized and understood to make the prediction model more robust. The multivariate
statistical tools enabled the effects of these process and equipment changes to be visible to the overall state of process stability.

Upon further examination of each of the three clusters, a prediction model was developed which showed that a relationship existed between the key process signals and the resultant cast polymer sheet thickness profile quality. This feat is significant in that this is the first time that this relationship has been established and demonstrated. Multivariate statistical techniques provide a unique capability for prediction model development. These tools have been historically untapped for process applications where significant value can be derived in establishing the key relationships between process conditions and the resulting product quality attributes.

**Organizational Issues Critical in Achieving Increased Quality Throughput**

Process improvement activities within the polymer operations are currently driven by machine teams or by process excellence teams (PETs). Each machine team is involved with process improvement efforts for their group of machines. The PETs work on process improvement activities for functional areas such as casting, coating, winding, and conveyance.

While each machine-based team works on improvement activities for their machines, more cross-team involvement for sharing and implementing consistent and similar process improvement practices among the various machine teams is needed. While each PET has attained near term improvements in their individual functional areas, these teams are primarily focused on improving their specific functional areas in the overall production process. Performance incentives are important to the operation to encourage and reward cross-functional learning among all of the engineers and operators, to foster the development of consistent process improvement practices from machine to machine, and to accomplish the implementation of these systematic process improvement practices across these machines. This can be achieved by critically assessing the similarities and differences across the machines and requiring that systematic operation practices be consistently developed, implemented, and utilized.
Process improvement activities within the operations have been primarily driven by machine-specific problems, whether these be machine focused or functional area focused. Benefits of systematic and holistic operating practices across the polymer operations, such as the asset utilization model, the process optimization framework, and the function-based process quality methods, can help the operations achieve the process improvements crucial to maintaining a competitive advantage by increasing quality polymer sheet throughput and reducing operating costs and overhead. Initially, these benefits and gains could be best accomplished by focussing on the low asset utilization number machines for these improvement efforts. Throughout the operations, increased efforts to implement continuous process improvement on a global scale and across all machines will depend upon the operations willingness to implement the performance incentives cited above to foster and reward cross-functional participation of all engineers and operators.
References