Improving the Manufacturing Yield of Investment Cast Turbine Blades through Robust Design

By

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B.S. Mechanical Engineering, Brigham Young University, 2003

Submitted to the Sloan School of Management and the Department of Mechanical Engineering in Partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration
AND
Master of Science in Mechanical Engineering

In conjunction with the Leaders for Manufacturing Program at the

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ABSTRACT

The manufacturing of turbine blades is often outsourced to investment casting foundries by aerospace companies that design and build jet engines. Aerospace companies have found that casting defects are an important cost driver in the price that they pay the foundries for the turbine blades. Defect types include porosity, stress, grain, fill, and mold-related defects. In order to address the defect problem, aerospace companies have adopted a design for manufacture approach to drive the cost of the turbine blades down.

The principal research objective of this thesis was to discover how the critical part features on the turbine blade drive the number of manufacturing defects seen in the casting process. This problem was addressed by first selecting and evaluating a casting simulation software package. Secondly, a robust design of experiments was performed by using the simulation software. In the experiment, the dimensions of the critical part features were varied in order to quantify how the critical part features relate to manufacturing defects.

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I would also like to thank my MIT faculty supervisors, Steven Eppinger and Daniel Whitney, both of whom made significant efforts in guiding and directing me during this research project. I will always appreciate their guidance and support.

In addition, I would like to thank Honeywell International Inc. for providing me with a laboratory where I could apply my learning while on internship. Specifically, Dr. Al Sanders and Mike Volas were extremely helpful in guiding and directing me at Honeywell.

Finally, I would like to thank my beautiful wife, Angie Margetts, for her unyielding support throughout my educational experience at MIT. Without her as a foundation to our family, my education at MIT would not have been possible. My daughters, Annabelle and Elizabeth Margetts, were also instrumental. Their smiling faces often buoyed me up during my graduate experience.
Biographical Note

I was born in Farmington, Utah. I attended Brigham Young University where I received a Bachelor of Science in Mechanical Engineering. While at Brigham Young University, I applied my learning while working as an intern for Dynapac Rotating Co. in Salt Lake City, Utah and for Micron Technology Inc. in Boise, Idaho. In addition to performing internships as an undergraduate, I spent two years in northern Italy serving a mission for my church.

After completing my undergraduate degree, I was hired as a mechanical engineer at Ultradent Products Inc. in South Jordan, Utah. While at Ultradent, I became interested in business management as I transitioned into a leadership role at the company. This led me to pursue the Leaders for Manufacturing program at the MIT Sloan School of Management and MIT School of Engineering in Cambridge, Massachusetts. The Leaders for Manufacturing program and its sponsoring companies provided me with the opportunity to do research and write this thesis while working as an intern at Honeywell International Inc. in Phoenix, Arizona.
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1. PART I: Introduction

1.1. Introduction

I wrote this paper as part of a 6-month internship that I performed at the aerospace division of Honeywell International Inc. (Honeywell) in Phoenix, Arizona. The Advanced Manufacturing Engineering (AME) group, a subdivision within the aerospace division, sponsored this research project. AME is primarily concerned with affecting product cost, product producibility, and product improvement. Their mantra is to facilitate discussion between design engineering and manufacturing engineering so that Honeywell’s products remain ahead of the competition from a cost and producibility standpoint.

In this paper, I will explore how to improve the manufacturing yield of investment cast turbine blades by employing an investment casting simulation software package called ProCAST coupled with a design of manufacturability method called robust design. Part I of the paper will give context and background to the problem of investment casting defects that typically affect investment cast turbine blades. Part II will illustrate the robust design process and present how it has been applied by others to improve products and processes. Part III will describe ProCAST, an investment casting simulation software package. This software package was evaluated and used as a substitute for actual casting defect data. Part IV will then describe a specific case where the robust design process was coupled with the casting simulation software in order to quantify how manufacturing defects are associated with design features on a specific turbine blade. Finally, Part V will conclude the paper with some final thoughts on the subject and recommendations to be applied in the future.

1.1.1. Problem Statement

Investment casting of turbine blades is challenging. Casting defects occur too frequently in turbine blades. Aerospace companies seek to design turbine blades that minimize the number of defects seen in the casting process because as the number of defects increases, the price that the foundries charge for the turbine blades also increases. In other words, the more
difficult the turbine blade is to manufacture, the greater the price the aerospace company pays for the turbine blade.

Honeywell spends millions of dollars each year on the turbine blades that it buys from investment casting foundries. Because of the magnitude of the dollar amount, many projects and programs that provide incremental improvement to the manufacturability of the blades are examples of money well spent. This has driven Honeywell to make significant efforts to establish practices that help the company design turbine blades that are more readily manufactured.

Honeywell would like to discover a few more levers that it can use to improve the manufacturability of its turbine blades. In this paper, I will illustrate a few additional tools that Honeywell can use to further improve the producibility of its turbine blades.

1.1.2. Investment Casting Process

Investment casting is one of the oldest manufacturing methods known to man. Archeologists have dated objects that were investment cast, or lost wax cast, to between 3000 – 2500 B.C. (Goodway, 1988). The manufacturing method of investment casting saw resurgence in the early 20th century. Currently, there are about 350 investment casting companies in the United States with many others scattered throughout the world (Paton, 2001). The investment casting technique is used throughout industry to cast near net shape parts that have dimensional accuracy of greater than plus or minus 0.005 in/in (Clegg, 1991).

The investment casting process is made up of 10 steps. First, a disposable wax part is formed in a mold and allowed to harden. The part is then removed from the mold and assembled on a tree of multiple parts. The tree is dipped into a slurry of fine ceramic particles called a wash coat. The wash coat is further coated with larger ceramic particles in a process called stuccoing. After the ceramic mold has dried, the mold is heated to allow the disposable wax part to melt out of the mold. The mold is then fired to give it strength and to preheat it in anticipation of the metal pouring process. Once the mold has reached a specified preheat temperature, metal is poured into the mold and allowed to solidify. Once the solidified metal
has cooled to a specific temperature, the ceramic mold is broken away from the metal parts in a knockout process. The metal parts are then removed from the tree in a cutting and grinding process. Finally, the parts are inspected to find any manufacturing defects that formed during the casting process. The entire investment casting process is depicted in Figure 1.

Figure 1: Steps in the investment casting process (Horton 253).

1.1.3. Turbine Blade History

The history of the development of turbine blades for aerospace applications is rich. It all began with Hans von Ohain’s and Sir Frank Whittle’s independent invention of the jet engine in the late 1930’s. Since the invention of the jet engine, turbine blade designers have known that significant advances in power and efficiency would be made through a two pronged approach, airfoil design and temperature resistance. A jet engine runs most efficiently when its airfoils are designed so that their shape produces the maximum amount of energy per weight of the engine. In addition to shape, the efficiency of the engine increases as the engine is able to run at higher and higher temperatures.

The turbine blade shape and temperature requirements have forced casting foundries to adapt to the jet propulsion industry’s ever changing needs. Since the invention of the turbine engine, turbine blade designers have continually pushed the manufacturing capabilities of
foundries. Foundries have had to learn how to cast complex turbine blade shapes, including shapes with difficult to cast internal cooling passages, and to work with an ever changing library of super alloy materials that satisfy the temperature requirements of a particular turbine blade design. Recent investment casting process improvements include vacuum induction melting, directional and single crystal solidification, and air cooling passage casting (Sims, 1987). These process improvements have driven significant performance increases in turbine blade technology.

The investment casting process is widely used throughout the aerospace industry to produce turbine blades and other engine components. In fact, one researcher estimated that in 1991 the parts produced specifically for the aerospace industry made up 65% of the investment casting market in the United States (Clegg, 1991). Others have given similar estimates. Another researcher identified the aerospace industry as the largest single user of the investment casting process with applications in turbine blades, turbine vanes, and turbine structural components (Horton, 1988). A few examples of turbine blades are shown in Figure 2. Some of the blades in the figure have very difficult to cast internal cooling passages while other blades have features that are much more straightforward to cast.

Figure 2: Examples of turbine blades (TurboCare, 2008).
1.1.4. Turbine Blade Description

Most turbine blades fall within one of four shape categories: unshrouded, shrouded, unshrouded cooled, and shrouded cooled. In general, this ordering reflects the difficulty to cast each of the blade types: unshrouded is the easiest to cast and shrouded cooled is the most difficult to cast. One researcher summed up this increasing manufacturing difficulty by stating “the occurrence of defects...has become more common with the increasing complexity of the components in the aerospace sector” (Shollok, 2006, p. 1338).

The shroud terminology simply describes whether or not the turbine blade has an outer surface that prevents gas from moving around the circular array of turbine blades as opposed to through the array. The cooled terminology describes whether or not the blade has internal cooling passages that force air to flow through the inside of the turbine blade. These four types of blades are depicted in Figure 3.

![Figure 3: Four types of turbine blade shapes.](image)

Because the experimentation in this thesis is primarily focused on a shrouded turbine blade, a further description of this type of blade is provided. This particular turbine blade consists of multiple parts. These parts are shown pictorially in Figure 4. The root is used as an attachment mechanism by which the turbine blade is mounted to a disc. Multiple blades are mounted on a disc to form an array of blades. The inner shroud is designed as an attachment mechanism for the blade and prevents gas from slipping by the inner part of the array. The
blade is designed as an airfoil to produce power as the hot gases expand through the jet engine. The blade is further described by its leading edge and trailing edge. The leading edge is closest to the combustion portion of the jet engine and the first to encounter the hot gases from the hot section of the engine. The trailing edge is on the opposite side of the blade and is the last point of contact of the hot gases. The outer shroud and its two knife edges are designed to prevent gas from slipping past the outer part of the array of blades.

![Diagram of turbine blade parts](image)

**Figure 4: Parts of a shrouded turbine blade.**

Turbine blades used in jet engines are primarily made of nickel based superalloys. Superalloys are defined as “an alloy developed for elevated temperature service...where relatively severe mechanical stresses are encountered” (Sims, 1987, p. 3). This class of materials is perhaps the most important factor in driving the jet engine to higher and higher performance levels. Nickel base superalloys went through a renaissance of discovery in the later portion of the first half of the twentieth century at the same time the jet engine was being developed. Examples of nickel base superalloys that find their roots in this early development and that are still used today at Honeywell include IN-713, IN-100, and IN-792. Development of these early materials continues today. Most advanced turbine blades that have internal cooling passages consist of proprietary material compositions that facilitate advanced solidification methods in the turbine blade.
1.1.5. Defects Found in Turbine Blades

Turbine blades are affected by defects that are universal to all castings but also experience microstructure related defects that are brought on by strict quality requirements. Examples of universal types of casting defects include shrinkage, porosity, distortion, and cracking. Examples of microstructure related defects include freckles, recrystallized grains, slivers, and bigrains. A list of defects that are commonly found in turbine blades is provided in Table 1. The defect types in the table are organized by defect relation: filling, porosity, stress, mold, segregation, and, grain.

<table>
<thead>
<tr>
<th>filling related defects</th>
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<tbody>
<tr>
<td>no-fill</td>
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<tr>
<td>entrapped gas</td>
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<tr>
<td>weld line</td>
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<table>
<thead>
<tr>
<th>porosity related defects</th>
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<tbody>
<tr>
<td>macroshrinkage</td>
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<tr>
<td>microporosity</td>
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<td>gas porosity</td>
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<tr>
<th>stress related defects</th>
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<tbody>
<tr>
<td>distortion</td>
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<td>cold crack</td>
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<td>hot tear</td>
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<tr>
<th>mold/core related defects</th>
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<tbody>
<tr>
<td>inclusion</td>
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<td>core shift</td>
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<tr>
<th>segregation related defects</th>
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<tbody>
<tr>
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<td>macrosegregation</td>
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<table>
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<tr>
<th>micro/grain structure related defects</th>
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<tbody>
<tr>
<td>equiaxed/directional/single crystal</td>
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<tr>
<td>grain size</td>
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<tr>
<td>high angle boundaries</td>
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<tr>
<td>multigrain</td>
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<tr>
<td>bigrain</td>
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<tr>
<td>misoriented grain</td>
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<tr>
<td>zebra grain</td>
</tr>
<tr>
<td>freckle</td>
</tr>
<tr>
<td>sliver</td>
</tr>
<tr>
<td>recrystallized grain</td>
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</tbody>
</table>

Table 1: Casting defects found in turbine blades (Yu, 2002).
Most of these defect types are difficult or impossible to simulate in casting simulation software at the present time. For example, a core shift defect is difficult to simulate. Core shift defects form when flowing molten metal moves the core that forms the internal cooling passages of a cooled turbine blade. The displaced core creates a wall thickness in the blade either too thick or too thin. The physical processes that govern this shifting behavior are difficult to simulate because of the random nature of the process. Casting simulation software such as ProCAST is only able to attempt to simulate a select few of the defects described in the table. These defect and their common location on a turbine blade are shown in Figure 5.

![Turbine blade casting defects](image)

Figure 5: Turbine blade casting defects that ProCAST attempts to simulate (Yu, 2002).

### 1.2. Design for Manufacture

Design for manufacture is defined by one group of researchers to mean the activities that facilitate “ease of manufacture of the collection of parts that will form the product” (Boothroyd, Dewhurst, & Knight, 2002, p. 1). Like others, they make a distinction between design for manufacture and design for assembly. For example, design for manufacture of a
turbine blade means to create a design where the ease of manufacture is maximized and the number of defect prone areas is minimized. In contrast, design for assembly of a turbine blade means to create a design where the turbine blade, mating hub, and fasteners are designed to maximize ease of assembly of the parts that form the array of turbine blades. These same researchers go on to further define design for manufacture by stating three activities for which it is used.

First, as the basis for concurrent engineering studies to provide guidance to the design team in simplifying the product structure, to reduce manufacturing and assembly costs, and to quantify the improvements. Second, as a benchmarking tool to study competitors’ products and quantify manufacturing and assembly difficulties. Third, as a should-cost tool to help negotiate suppliers’ contracts (Boothroyd, Dewhurst, & Knight, 2002, p. 1).

The importance of design for manufacture and its applicability to Honeywell was emphasized by Rob Gillette, President and CEO of the aerospace division of Honeywell. He once said that 85% of cost of a product is set in stone by the end of the Honeywell’s Integrated Product Delivery and Support phase two (Defense Advanced Research Projects Agency, 2008). At the end of this second step in Honeywell’s seven step product development sequence, only the product’s concept definition is prescribed. Specification and detailed development of the product have not even begun at this point. Other academic researchers agree in principle with this statement. One such researcher said “the decisions made during the design process have a great effect on the cost of a product” (Ullman, 2003, p. 4). Design for manufacture is important to Honeywell because it is a significant tool that the company can use to affect the time, effort, and money it takes to produce a product. Although the tools used in design for manufacture are currently not utilized until the specification and detailed development stages of the Honeywell’s product development sequence, a particular design and its associated manufacturing processes are still malleable at this point. The part can be significantly influenced by the tenets of design for manufacture at these early stages of development.

1.2.1. Design for Manufacture for Honeywell Turbine Blades

In the past, aerospace companies have taken two approaches to design for manufacture of turbine blades, expert information and design guides. Recently, a few of these companies
have experimented with a third mechanism in a repertoire of design for manufacture tools, investment casting simulation. Details of these techniques are summarized in the following three sections. Although the first two techniques, expert information and design guides, have been somewhat effective in combating design for manufacturability issues of turbine blades, there still remains much work to be done to further combat the problem. These two approaches remain insufficient. Aerospace companies still release turbine blades to their contract manufacturers and later find that the parts contain design for manufacture flaws that could have been avoided.

The research in this paper will outline a few more tools that aerospace companies can use to identify the elusive design for manufacture issues that are not identified through expert information and design guides. These two tools, casting simulation software and robust design, can be used by aerospace companies during the initial stages of the design process to anticipate manufacturing issues that will be encountered in the future. In addition, actual investment casting defect data could be used as a tool to identify design for manufacture issues in turbine blades. Unfortunately, this defect data is difficult to obtain from investment casting foundries. These foundries are hesitant to share defect data because they believe the defect data is proprietary information.

1.2.1.1. **Expert Information**

Aerospace companies have employed various forms of expert information to combat design for manufacture issues in turbine blades. First, companies have hired investment casting experts to consult with design engineers in order to create turbine blades that are more easily manufactured. These investment casting experts were previously employed by the turbine blade suppliers and bring years of hands on expertise to their roles. Second, companies will sometimes partner with their investment casting suppliers to work on trouble areas of specific turbine blade designs in concurrent engineering efforts. Third, the turbine blade design community at a particular company uses its knowledge that is based on past experience to design blades that are more readily manufactured. Finally, these same engineers will at times visit the turbine blade supplier to obtain hands on experience.
1.2.1.2. Design Guides

In addition to undocumented expert information, documented design guides have also proven useful in creating designs consistent with design for manufacture principles. Trucks (1974) and Spinosa (1999) have written in academic literature about various rules and tolerance guidelines for investment casting. Honeywell’s suppliers have also provided guides that are tailored specifically for investment cast turbine blades that provide further rules and tolerance guidelines. Likewise, Honeywell has documented expert information in turbine blade design guides that were created for internal use at Honeywell. Honeywell has also taken its design guide one step further and created a design for manufacture scorecard. The scorecard helps mechanical designers understand the trade-off between performance and manufacturability by quantifying the difficulty of producing the features they choose for the design. The scorecard is used during conceptual design studies.

1.2.1.3. Simulation

The investment casting simulation software package, ProCAST, was purchased on a trial basis to be evaluated and tested. This software was purchased in part because of recommendations that Honeywell obtained from its turbine blade suppliers. These suppliers regularly use the software to evaluate the manufacturing difficulty of a particular turbine blade.

1.2.2. Evaluation of Design for Manufacture for Honeywell Turbine Blades

Although expert information and design guides are good tools that can be used to combat design for manufacture issues, they remain insufficient to identify all design for manufacture issues. Each tool has weaknesses. First, the quality of the expert information is inherently based upon the experience of the person with the knowledge. It is difficult to find a manufacturing expert that knows all of the design and manufacture issues that affect investment castings. Manufacturing experts or trained design engineers may have a large breadth of training but they lack some training that is critical to identify all the design for manufacture issues. Second, changes in the industry are difficult to anticipate. Investment casting foundries change their manufacturing processes through continuous improvement
efforts. Manufacturing experts do not have hands-on experience with the new processes so they cannot foresee all the manufacturing problems that will be encountered from the new processes. Finally, the handoff of information between manufacturing experts and design experts does not always occur optimally. Cultural, political, or functional issues may exist between the two working groups that prevent information from freely flowing between the groups.

Design guides also have weaknesses. Like expert information, design guides do not contain all of the design for manufacture issues that will be encountered in practice. The guide is based upon an expert’s vast industry knowledge but it remains incomplete because the expert does not know everything. In addition, manufacturing experts cannot convey tacit information. The expert who writes a design guide is unable to convey all of his or her knowledge on paper. Finally, design guides are cumbersome to create and update. Changes in the investment casting process will be overlooked because the design guide simply does not contain all of the latest information that is relevant to the industry.

1.3. Turbine Blade Industry

The market for investment cast turbine blades is dominated by two companies, Alcoa Howmet (Howmet) and Precision Castparts Corp. (PCC). This same sentiment is shared by Howmet and PCC. In fact, PCC acknowledged only Howmet as their primary competitor by stating “our principal competitor is Howmet” in its 2000 10K filing to the Securities and Exchange Commission (PCC, 2000, p. 12). Likewise, Howmet only recognized PCC by stating “PCC, a publically held company in Portland, Oregon, is [our] primary competitor” and then go on to say “Howmet and PCC account for most of the total aerospace turbine engine and industrial gas turbine investment casting production” in its 2000 10K filing (Howmet, 2000, p. 4).

Although Howmet and PCC clearly dominate the market today, both acknowledged other small private foundries like ESCO Corp. In addition to small foundries, both PCC and Howmet agree that international competition has begun to increase as governments have instituted laws that require purchasing obligations with respect to products that are
manufactured in their home countries. International companies are gearing up to be competitive in the years to come.

Howmet has the greatest market share of the investment casting airfoil business. In fact, PCC stated “Howmet is believed to hold in excess of 50 percent of the total market for cast airfoils” (PCC, 2000, p. 12). Howmet also recognized this same fact by saying “[Howmet] believes it has a majority market share in the overall worldwide aerospace and industrial gas turbine engine airfoil investment casting market” (Howmet, 2000, p. 4). Exact sales figures for investment cast turbine blades specifically used in aerospace applications are not reported by either company but both companies do report total investment casting sales and aerospace industry sales. These sales figures are reported in Table 2. It should be noted that Howmet’s only line of business, at the time of the reported sales figures, was investment casting (Howmet, 2000). In contrast, investment casting only made up 58% of PCC’s total sales (PCC, 2000).

<table>
<thead>
<tr>
<th>Howmet</th>
<th></th>
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<tbody>
<tr>
<td>total sales</td>
<td>$1,459</td>
</tr>
<tr>
<td>investment casting sales</td>
<td>$1,459</td>
</tr>
<tr>
<td>aerospace sales</td>
<td>$733</td>
</tr>
<tr>
<td>*year ending December 31, 1999</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Precision Castparts</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>total sales</td>
<td>$1,673</td>
</tr>
<tr>
<td>investment casting sales</td>
<td>$971</td>
</tr>
<tr>
<td>aerospace sales</td>
<td>$836</td>
</tr>
<tr>
<td>*year ending April 2, 2000</td>
<td></td>
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</table>


Sales are awarded through contracts. Most contracts between jet engine manufacturers and their investment casting contract manufacturers are awarded through a competitive bidding process. Although the length of individual contracts varies, most contracts span multiple years with some as long as three years. Most contracts include provisions that require the customer to order exclusively from the contract manufacture. Typically the price set in the contract is periodically reduced as the investment casting contract manufacture experiences cost reductions through learning.
1.3.1. **History of Dominant Turbine Blade Foundries**

The history of the turbine blade investment casting industry is a history of growth and consolidation. In addition to internal growth, Howmet and PCC, the two dominant companies in the industry, have either acquired smaller investment casting related companies or have been acquired themselves by other industrial conglomerates throughout their respective histories.

Howmet, originally established as the Howe Sound Company, established itself early in the growth of the turbine blade investment casting industry by acquiring other companies. Since this early growth, the company has been so attractive that since 1975 it has been acquired by three large industrial companies. The acquirers include Pechiney, Thiokol, and Alcoa. Throughout these acquisitions, Howmet has remained as one of the dominant two companies in the turbine blade investment casting industry.

Likewise, PCC has experienced substantial growth since its inception. Since going public in 1968, PCC has acquired over 25 companies. Some of these acquisitions related to the aerospace industry include Centaur Cast Alloys, TRW’s cast airfoils division, Advanced Forming Technology, Wyman-Gordan, United Engineering Forgings aerospace division, SPS Technologies, and Air Industries Corp. (Hoovers, 2008). Each of the acquisitions fueled the growth of PCC’s investment casting business and helped the company establish itself as one of the dominant companies in the industry.

1.3.2. **Outsourcing Trap**

Howmet and PCC are the top producers of turbine blades in the world. The majority of aerospace companies use these companies to cast their turbine blades. By outsourcing to these two companies, aerospace companies have become dependent on these suppliers to deliver quality turbine blades for the jet engines that they design and build. Although the relationship has been mutually beneficial over the years, the aerospace companies have become a victim of an outsourcing trap. As described previously, both Howmet and PCC are hesitant to share any of the defect data that has been compiled for turbine blades. In essence,
many companies have little leverage with the two large investment casting suppliers whose sales volumes are primarily generated by General Electric and United Technologies. This knowledge based outsourcing trap has hindered Honeywell’s ability to build and implement design for manufacture tools for turbine blades.

Business management literature is ripe with research related to the term outsourcing trap because of the recent popularity of outsourcing manufacturing to contract manufacturers. Unfortunately, many company executives have not been exposed to this academic knowledge base. Too often, companies have justified outsourcing by simply recognizing it as a means to help the company focus on their core business, to reduce costs, or to increase competitive advantage. Although many outsourcing strategies are financially beneficial to companies, the executives fail to recognize that an outsourcing strategy comes at a price.

When speaking of the outsourcing trap, a number of researchers noted “organizations fail to realize the impacts on their people, processes, methods, and tools as they proceed down the outsourcing path” (Power, Bonifazi, & Desouza, 2004, p. 37). These same researchers go on to say that many companies fail to perform due diligence with respect to how data and intellectual property rights, two key outsourcing success factors, will be handled by the two parties (Power, Bonifazi, & Desouza, 2004). This problem, as described above, is exactly what many aerospace companies currently face. By outsourcing turbine blade manufacturing, the companies have positively affected their ability to focus on their core business but have negatively affected their ability to create design for manufacture tools that support their core business. The companies have lost access to the key investment casting defect data that would be useful in creating powerful turbine blade design for manufacture tools that are based on real defect data.

1.3.3. Outsourcing Trap Remedy

Aerospace companies currently find themselves in a situation where if they seek to further pursue this key investment casting defect data, the companies will have to take corrective measures. A three step pathway to remedy this defect data knowledge asymmetry is presented below.
First, due diligence should be done on the contract manufacturer before entering contract negotiations in order to better understand the turbine blade contract manufacturer. During this research, aerospace companies should seek to understand the contract manufacturer’s company structure, business model, and past business practices so that future contract negotiations with the vendor can be informed by their business paradigm. Some of this information can be obtained from the companies public records but the most important information will be unstated. This unstated information must be obtained by speaking with the contract manufacturers face to face.

Second, aerospace companies should seek to understand the incentives to which the contract manufacture will respond. The contract manufacture might be open to defect data sharing if the aerospace company is willing to pay a small price for the information. Perhaps a slight increase in the price of the investment cast components is warranted if the contact manufacture is willing to share the defect data. In addition, the contract manufacture may respond with defect information if the aerospace company is willing to extend the length of the contract beyond the typical contract length.

Third, future contracts between aerospace companies and the contract manufacture should be scrutinized and adjusted. Future contracts should be written with a clause that calls for manufacturing defect data sharing in exchange for the incentives identified in step two. In addition to the official contract, aerospace companies should seek to establish and continue to build a relationship of trust with the contract manufacture. Informal team building activities such as dinners and recognition events are examples of actions that can go a long way in establishing a relationship where information is readily shared.

Ultimately, a real time manufacturing data system much like Cisco’s Autotest, a manufacturing information system implemented in the factories of Cisco’s contract manufacturers, would ideally put in place. This internet based system can be used to monitor the productivity, defect count, defect type, and other manufacturing metrics that occur on any piece of manufacturing equipment at the contract manufacture. Although this system would
ultimately support the aerospace company’s supply chain team, it could also be used to garner the key investment casting defect data that the company seeks for its design for manufacture tools.

1.4. Summary

In this part of the paper, I introduced the investment casting defect problem that many aerospace companies face when designing turbine blades for use in jet engines. As stated, there are many types of defects that plague turbine blades during the investment casting process. The defect types include filling, porosity, stress, mold, segregation, and grain related defects. Design for manufacture tools are used to minimize the defects. In addition, actual defect data can be used to learn how to decrease the defects. Defect data is difficult to obtain and aerospace companies will have to take corrective action in the future in order to garner the data.

The remaining parts of the paper will describe more fully the two design for manufacture tools, robust design and simulation software, that were introduced in this part of the paper. First, the technique of robust design will be described in detail. Second, investment casting simulation software will be introduced and evaluated. Finally, the two tools will be coupled in a specific case study. The paper will then conclude with some final recommendations.
2. PART II: Methodology

This part of the paper describes the robust design methodology. This methodology, based on design of experiments (DOE), is employed in experimentation to improve the performance of products and processes. Robust design seeks to maximize the performance of a product or process while minimizing the random effects of noise, uncontrolled variation.

2.1. Design of Experiments

The first formal use of statistical methods applied to experimental design was proposed by Sir Ronald A. Fisher at the beginning of the twentieth century. His method quickly grew in popularity. Although DOE was first applied to agricultural science, it is now widely accepted and used in many academic disciplines including engineering, physical science, biology, medicine, social science, and others.

Montgomery defined the method of DOE as “the process of planning [an] experiment so that appropriate data will be collected, which may be analyzed by statistical methods resulting in valid and objective conclusions” (Montgomery, 1976, p. 2). In the experiment, several factors are identified as having an effect on the outcome of the experiment. The DOE process seeks to provide a structured method to determine the specific setpoints of the control and noise factors that maximize the desired outcome of the experiment. The DOE method is an efficient and objective approach to analyzing the factors that influence the results of an experiment.

The exact DOE method will not be described in detail in this paper because robust design, a method based on the principles used in DOE, will be described in the sections that follow this section. In order to best understand the DOE method, the reader should review the many texts dedicated to the subject that have been written and published throughout academic literature.
2.2. Robust Design Literature Review

Most texts that describe the robust design process break the process into several steps. By breaking the process into prescribed steps, the experimenter is able to easily administer the robust design method to a product or process. Four books and the step by step robust design method they propose are shown in Table 3.

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>1 - identify control factors, noise factors, and performance metrics</td>
<td>1 - selection of factors and/or interactions to be evaluated</td>
<td>1 - statement of the experimental problem</td>
<td>1 - recognition of and statement of problem</td>
</tr>
<tr>
<td>2 - formulate an objective function</td>
<td>2 - selection of number of levels for the factors</td>
<td>2 - understanding of the present situation</td>
<td>2 - choice of factors and levels</td>
</tr>
<tr>
<td>3 - develop the experimental plan</td>
<td>3 - selection of the appropriate orthogonal array</td>
<td>3 - choice of response variables</td>
<td>3 - selection of a response variable</td>
</tr>
<tr>
<td>4 - run the experiment</td>
<td>4 - assignment of factors and/or interactions to columns</td>
<td>4 - choice of factors and levels</td>
<td>4 - selection of experimental design</td>
</tr>
<tr>
<td>5 - conduct the analysis</td>
<td>5 - conduct tests</td>
<td>5 - performing the experiments</td>
<td>5 - performing the experiment</td>
</tr>
<tr>
<td>6 - select and confirm factor set points</td>
<td>6 - analyze results</td>
<td>6 - data analysis</td>
<td>6 - data analysis</td>
</tr>
<tr>
<td>7 - reflect and repeat</td>
<td>7 - confirmation experiment</td>
<td>7 - conclusions and recommendations</td>
<td>7 - conclusions and recommendations</td>
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</table>

An investigation of each of the methods shown in Table 3 reveals that they are all remarkably similar. Each has a few steps where the experiment is planned, a step where the experiment is carried out, and a few steps where the experiment is analyzed. This paper will describe the process proposed by Ulrich and Eppinger in further detail in the following sections.

2.2.1. Identify Control Factors, Noise Factors, and Performance Metrics

The experimenter first needs to identify the control factors, noise factors, and performance metrics related to the experiment. The factors that influence the outcome of the experiment are divided into two types: control factors and noise factors (Mukerjee & Wu, 2006). Control factors are the factors that can be controlled by the experimenter. Control factors are fixed once they are selected. In contrast, noise factors cannot be controlled by the design team. Noise factors are variables that are difficult or impossible to control. In general, two or three levels of the control factors are specified for the robust design experiment. The performance metric is the measured outcome of the experiment.

A group of researchers provided an example that describes the three parameters when they illustrated an experiment to improve the yield of a chemical process (Mukerjee & Wu, 2006). The control factors in the experiment were reaction temperature, reaction time, catalyst type, and catalyst concentration. The level of each of these factors could be explicitly set by the experimenter. On the contrary, the noise factors that could not be controlled in the experiment were the purity of the reagent and the purity of the solvent stream. The experimenters used the reagent and solvent with knowledge that their purity had a tolerance band that could not be controlled. This uncontrolled tolerance is considered a noise factor. The performance metric of the experiment was the yield of the chemical process.

The experimenter can utilize a few tools to best understand the control factors and noise factors that influence the performance metric of the experiment. Two of these tools, parameter diagram and cause effect diagram, are depicted in Figure 6. These diagrams help the experimenter visualize the experiment. Factors and metrics can easily be added and subtracted from the diagram until the experimenter is comfortable with the control factors, noise factors, and performance metrics that will be used in the experiment.
2.2.2. **Formulate an Objective Function**

The performance metric should be translated into an objective function. Ulrich and Eppinger (2008) outline four different types of objective functions: maximizing, minimizing, target value, and signal-to-noise ratio. The experimenter must select an objective function in order to specify the goal of the experiment. The analysis of the experiment and the subsequent selection of factor setpoints depend on the objective function. In the example chemical process, the yield was to be maximized.

2.2.3. **Develop the experimental Plan**

One researcher noted “a mathematical model for the experiment must also be proposed, so that a statistical analysis of the data may be performed” (Park, 1996, p. 43). After the control factors, noise factors, performance metrics, and objective functions are specified, the experimenter must formulate an experimental plan that will form the backbone of the robust
design experiment. The experimenter has several choices. These choices include full-factorial, fractional-factorial, and orthogonal array designs. Because of time and money constraints, one group of researchers noted "fractional factorial and orthogonal arrays are often employed in conducting the experiments" in a robust design experiment (Wu & Chang, 2004, p. 436).

Although fractional factorial experimental plans are used in robust design, orthogonal arrays are more frequently used because of their efficiency. Orthogonal arrays are the smallest subset of fractional factorial designs that allow the experimenter to determine the main effects of the control factors. One experimental plan that is often used in robust design, an L8 orthogonal array, is shown in Table 4. The 1’s in the table represent a low control factor setting and the 2’s in the table represent a high control factor setting. For more details on how the control factors and noise factors should be assigned to columns, the reader should consult a robust design textbook like Ross (1998) or Park (1996) have written.

![Table 4: Example orthogonal array experimental design.](image)

### 2.2.4. Run the Experiment

The experimenter is ready to conduct the test after the experiment has been specified by the first three steps described in the previous sections. During the data collection process, the experimenter should proceed according to the experimental plan and should ensure that each test is performed in a uniform environment. In addition, the experimenter should randomize the runs in order to ensure that the test results are not biased.
2.2.5. Conduct the Analysis

There are numerous ways to analyze the experimental results. Ross (1998) describes a powerful robust design analysis tool called analysis of variance. He also introduces methods that build on analysis of variance like percent contribution of each control factor to total variation. Other more simple analysis methods include observing the experimental runs and ranking their outcome.

Ulrich and Eppinger (2008) suggest an analysis of means approach to test the main effect of each control factor. This approach is both simple and powerful. In order to perform an analysis of means, the experimenter averages the objective function at each factor level. For example, in the case of the chemical process, the yield would be averaged for all runs where the reaction temperature was set to low and for all runs where the reaction temperature was set to high. After calculating the averages, the results should be plotted for the control factor at its high and low setting. This same calculation and plotting technique should be repeated with all remaining control factors: reaction time, catalyst type, and catalyst concentration. To illustrate an example, I created data points from the chemical process previously introduced. The example graph generated by this method can be seen in Figure 7.

The graph in Figure 7 gives clear visual clues as to the best control factor settings and to which control factors are most important in effecting the objective function. By graphing the results, the experimenter clearly sees the most important control factors and those that are
less important. In the case of the chemical process shown in Figure 7, the temperature control factor should be set to low and should be recognized as the most important control factor that contributes to the yield. The graph shows that as the temperature changed from the low setting to the high setting, the yield decreased from about 90% to about 20%. The rest of the factors should be similarly analyzed in order to determine their best setting. It should also be noted that the rest of the control factors do not have a dramatic effect on the yield as compared to the temperature control factor. As these control factors moved from a low to high setting, there was little effect on the yield.

Ulrich and Eppinger (2008) also suggest that each control factor be subjected to an analysis of robustness. In this analysis, each control factor is tested to see which setting is able to minimize the range of the objective function as each noise factor changes. The experimenter may find that a particular control factor setting may maximize the objective function but the same control factor setting may not be robust to variation produced by the noise factors. In order to test for robustness, the experimenter should calculate and graph the average range of the objective function as the noise factor is allowed to vary. If the range is both a small percentage of the objective function and is minimized for the ideal setting of the control factor then the control factor setting is considered robust.

Once again, the data points that I created for the chemical process were used to illustrate an example. These data points are shown in Figure 8. The visual representation allows the experimenter to quickly identify the control factor setting that give robust results. In this particular case, reaction temperature, the most important control factor, should be set to low in order to minimize the variation produced by the noise factors. The analysis of means results likewise showed that the reaction temperature should be set to low in order to maximize the yield. Therefore, there is no trade off between choosing a setting that both maximizes the yield and minimizes the effect of the noise factors. This is not always the case. For example, in the case of the reaction time control factor, the analysis of means graph in Figure 7 shows that the setting should be set to low in order to maximize the yield but the robustness graph in Figure 8 shows that the setting should be set to high in order to
minimize the effect of the noise factors. In this case, there is a tradeoff that has to be made between performance and robustness.

![Range Yield: Chemical Process](image)

Figure 8: Robustness analysis graph for an example chemical process.

2.2.6. Select and Confirm Factor Setpoints

After the analysis of means and analysis of robustness is performed for each control factor, the experimenter is able to select the control factor setpoints. As was demonstrated in the previous section, the experimenter will have to identify the ideal control factor settings by examining the analysis of means and the analysis of robustness results. In many cases, tradeoffs will have to be made. After analyzing the results and the tradeoffs between performance and robustness, the control factor settings should be finalized and selected.

2.2.7. Reflect and Repeat

In many cases, the experiment can be rerun if time and money constraints do not preclude additional experimentation. While running further experiments, less important control factors should be eliminated in order to fine-tune the most important control factors. Additionally, further tests could include confirmation runs, interaction testing, and further performance/robustness tradeoff testing. Reflection on the experiments will also prove valuable. While reflecting, the experimenter should reconsider whether or not the correct control factors, noise factors, and performance metrics were adequately tested.
2.3. Application of Robust Design

Robust design has been applied throughout academia and industry to various products and processes in order to optimize the performance of the products and processes. Robust design is widely used because it is relatively easy to understand and apply. The process in turn yields powerful results. The insightful results are generated because the technique tests both controlled and uncontrolled factors that influence the outcome of an experiment. Robust design also minimizes the number of experimental runs that must be performed. Therefore, experimental time and experimental effort are minimized. The following section is a literature review that summarizes a few cases where robust design has been successfully employed.

2.3.1. Robust Design Case Study Literature Review

Phadke's (1989) text is often quoted throughout quality engineering literature. In his text he describes the robust design process with numerous examples that give a clear picture of how to apply the process. The book gives practical advice on how to set up, run, and analyze a robust design experiment. Perhaps the most noteworthy example in his text is an example in which he describes the robust design process when it was successfully applied to a chemical vapor deposition process.

Ulrich and Eppinger (2008) build on Phadke's work and describe how the robust design process can be used to enhance the product design and development process. Although their text primarily focuses on the product design and development, it includes a robust design chapter to demonstrate how the process can be used to improve the design of products. The text describes how products can be designed to be insensitive to random uncontrollable noise factors. Like Phadke, they use an example to describe the robust design process. The example they describe comes from a development group at Ford Motor Company in which the robust design process utilized simulation software to optimize the design of an automobile's rear seat belt.

Park (1996) also wrote a practical text that describes the utility of the robust design process much like the two texts previously described. This text, another excellent robust design
reference, is divided into several chapters that describe numerous examples of how to set up and run a robust design experiment.

Of particular note is Roy's (2001) text in which he utilizes a software package that aids the reader in applying the robust design process. He describes sixteen steps which help to establish product and process improvement. One of the steps is a detailed description of the robust design process. The text also reinforces learning by applying quality improvement methods to case studies from the automotive, machine tool, and welding industries.

Although many significant texts have been written on the subject of robust design, perhaps the easiest to understand is Ross's (1998) treatment of the subject. His book clearly describes the process of setting up, running, and analyzing a robust design experiment. His text is especially insightful with regards to analysis of variance. With his simple writing style, he helps the reader to readily understand how to analyze the results of a robust design experiment.

In addition to formal texts on robust design, numerous academic papers have been written that describe insightful applications of the method. A paper written by Wu and Chang (2004) has particular application to Honeywell's investment cast turbine blade designs. In their paper, they detail how robust design was successfully applied to a die cast component used as the enclosure of a personal digital assistant. In their treatment, they focus on how to properly perform an analysis of means and analysis of variance.

Muzammil, Singh and Talib (2003) present a paper that describes the optimization of a gear blanking process by using robust design. The paper describes the various factors that dictate the quality of the part. The authors then formulate a robust design process to optimize these factors. In particular, this paper demonstrates how robust design is properly applied to a manufacturing process.

Another example of a paper that addresses a robust design experiment that was performed in simulation software was written by Chen and Chen (2006). In their paper they describe a
simulated study that examines the plastic deformation behavior of sheet metal as it travels through a set of forming dies. Chen and Chen's study is similar to the study that was performed for this thesis.

2.4. Summary

In this part of the paper, I introduced the method of robust design. The technique is based on DOE and is used to improve the performance of both processes and components. The first step in the robust design process includes developing an experimental plan by identifying control factors, noise factors, performance metrics, and an objective function. Next, the experiment is carried out. Finally, the experiment is analyzed through an analysis of means and an analysis of robustness. As described, the robust design technique has been employed widely in academic writing.

The next part of this paper will introduce the principal conduit of experimentation for this paper, investment casting simulation software. The software will be described and evaluated. In addition, a few independent evaluations of the software will also be presented.
3. PART III: Experiments

This part of the paper describes a specific investment casting simulation software package called ProCAST that is made by ESI Group. The software is widely used in the casting industry to gauge the manufacturability of components that will be cast. The software was used in this research project to better understand how specific design features on an investment cast turbine blade are related to investment casting defects.

3.1. Casting Simulation Software

The advent of casting simulation software has changed how investment cast parts are designed and manufactured. Computer simulation of casting has been successfully applied to numerous designs across many industries. For example, Howmet uses the software at its primary research facility to improve its investment casting techniques. It is able to significantly reduce the time and money spent on process development by simulating the investment casting process. In many cases, these companies can test their processes without incurring the cost of actually pouring molten metal. Costly trial and error methods are minimized.

In addition, investment casting simulation software is used by foundries to identify potential defect areas in a casting design that could prove detrimental to the turbine blade. By identifying the features that are apt to produce casting defects, they can improve the quality and the yield of the turbine blades.

Although investment casting simulation software has come a long way since its inception, it still has limitations. Casting simulation software is unable to precisely simulate the casting process. It is able to come close but there remains room for improvement. For example, the casting process of a freight trailer’s locking jaw was performed in ProCAST by Sholapurwalla (2002). The researcher compared a simulation study to an actual study where metal was poured. The researcher found that the casting simulation was able to predict the general area where a no fill defect would occur but the software could not predict the exact size and
location of the defect. The general indication provided by the software was sufficient to identify and eliminate the potential problem area in the casting.

3.1.1. History of Casting Simulation Software

Although algorithms to simulate solidification of cast ingots were used as far back as 1930, it was not until the advent of the computer in the 1960s that detailed casting simulations were achieved (Yu, 2002). Steady advances since the 1960s have been made in the study of casting simulation. Today, many foundries consider casting simulation software to be an essential tool for their business.

The development of ProCAST started in 1986. Since that time, updates and improvements have been made to the software through multiple releases. The software is currently on a six month release schedule. One major and one minor release are made per year. The major release often makes changes to both the calculation algorithms and the user interface while the minor release is much like a software service pack that is used to iron out small functionality problems. The major releases include major enhancements like user interface updates and additions to the physics based models like the porosity indicator or the hot tear indicator. Minor releases fix bugs and improve other minor aspects of the software.

3.1.2. ProCAST Casting Simulation Software

ProCAST is made by ESI Group, a company based in France that has developed multiple lines of simulation software. Their portfolio includes software to simulate casting, stamping, welding, crash testing, aerodynamics, biometrics, electromagnetism and acoustics. ProCAST is their version of casting simulation. Like most casting simulation software packages, ProCAST uses a multistep process to simulate the investment casting process. This multistep process is depicted in Figure 9.
The first step is to create a CAD file that represents the geometry to which the casting simulation will be applied. ProCAST, like most casting simulation software packages, is able to accept all of the universal CAD formats like Parasolid, IGES, or STEP formats.

The second step is to input the CAD geometry into MeshCAST, a finite element analysis mesh generator. Once the model is input into MeshCAST, the user is able to specify various aspects of the mesh to best represent the original CAD geometry. Specifically, the user is able to specify the average density of the mesh, indicate areas of the geometry where the mesh will be more or less dense than average, create a boundary layer mesh on the surface of the geometry, and generate additional mesh to simulate the shell of the investment cast mold.

Third, the user inputs the mesh geometry into PreCAST where initial conditions and boundary conditions are specified for the casting simulation. There are over one hundred initial conditions and boundary conditions that can be controlled in ProCAST. The most important conditions that must be selected are metal material, mold material, heat transfer settings, initial metal temperature, initial mold temperature, ambient settings, and gravity settings. Other settings, specified by ProCAST for an investment casting simulation, are automatically fixed by the software but they can be manipulated.

Next, the user inputs the mesh geometry, initial conditions, and boundary conditions into the ProCAST solver. The ProCAST solver makes numerous calculations at various time
intervals in the simulation. Specifically, the complete ProCAST solver couples three distinct solvers: flow solver, thermal solver, and stress solver. The output of these three combined solvers is used to predict various casting defects like those listed in Table 1 and shown in Figure 5. Specifically, ProCAST has functionality to predict the following defects: no fill, weld line, porosity, distortion, and hot tear defects.

Finally, the results are viewed in the concluding step of the simulation called ViewCAST. Within ViewCAST the user is able to manipulate and view contour plots that depict the areas of the investment casting that are susceptible to investment casting defects. Figure 10 is an example of a turbine blade’s distortion contour plot that was generated by ProCAST. This is just one example of the over 25 different contour plots that can be viewed after the ProCAST analysis is complete. Other contour plots include temperature, fraction solid, solidification time, porosity, fluid velocity, pressure, thermal, solidification percent, principle stress, displacement, and hot tear contour plots.

Figure 10: Example distortion contour plot of a turbine blade. Units in cm.
3.1.3. **ProCAST Evaluation**

I evaluated ProCAST based on multiple criteria. These criteria were selected by a few of Honeywell's simulation and investment casting experts. In the following section, I present the evaluation criteria and discuss the results of the evaluation.

### 3.1.3.1. **Defect Prediction**

ProCAST claims to be able to accurately predict multiple types of casting defects. These defects include porosity, hot tear, distortion, no fill, and weld line defects. In order to first understand whether or not these types of defects could be predicted, I conducted a literature review to ensure that the models used by ProCAST were physics based models.

The ProCAST porosity prediction model uses a method developed by a number of researchers (Pequet, Gremaud, & Rappaz, 2002). The model is based on the solution of Darcy's equation that describes how fluid flows through a porous medium. The prevention of fluid flow is the primary mechanism that causes porosity to form in a casting. As a casting solidifies, molten metal is not always able to fill small voids where the casting has partially contracted. Porosity forms in the areas where the molten metal cannot backfill the small voids.

The hot tearing prediction model used by ProCAST was developed by another group of researchers (Rappaz, Drezen, & Gremaud, 1999). This prediction model uses a mass balance of the liquid and solid phases during solidification to account for the tensile deformation of the casting during solidification. As the casting cools, cavitation may occur when the deformation rate of the metal reaches a critical magnitude. This magnitude of deformation rate is used as an indication of whether cavitation, the impetus of a hot tear, will occur. The magnitude of deformation is used as an indication of hot tearing.

Distortion prediction by ProCAST is based on methods described by Chandra (1995). In the approach, a coupled thermo-mechanical analysis is performed to calculate the distortion experienced by the part. The model accounts for the release of latent heat, microstructural...
evolution, thermo-mechanical interaction between the metal and mold, heat loss from the mold surface, shrinkage allowance, and residual stresses.

No fill defects and weld line defects are simulated by solving the Navier Stokes fluid flow equations as the metal flows and cools in the casting. No fill defects form when the molten metal has reached a temperature where the metal is in a mushy state. In this state, the solid fraction solid is too high to allow the metal to adequately flow. Weld line defects form when two fronts of semi-liquid metal touch but do not thoroughly join. ProCAST uses a combination of the thermal solution and fluid flow solution, Navier Stokes equations, to determine the parts of the casting that are susceptible to these two types of defects.

In addition to evaluating the physical models that ProCAST uses to predict defects in castings, I performed a simulated test to evaluate ProCAST’s ability to predict each of the five defects described above. In the test, I created a theoretical part in order to force each of the five defects to occur. This theoretical part was designed with difficult to cast geometric features. The output of the software was then examined to see if the five defects were actually predicted. The theoretical part and its associated thermal contour plot are shown in Figure 11. Each defect type and each defect type’s probable location of occurrence are also shown in the figure.

![Figure 11: Theoretical part that was designed to force each labeled defect to occur.](image)

In the simulated test, I found that porosity, hot tear, and distortion defects were predicted but flow related defects, no fill and weld line, did not form in the theoretical part. Based on the design of the part, all of the defects should have been predicted. Further investigation into the assumptions that ProCAST uses to solve the Navier Stokes flow equations showed
that flow related defects are poorly predicted. The software must make significant simplifying assumptions in order to solve the equations. In the case no fill defect prediction, the software must assume that the molten metal fluid slips at the fluid wall interface because of the difficulties associated with generating sufficient mesh resolution in the regions where the boundary layer effects need to be simulated. Therefore, filling will always occur regardless of the complexity of the part’s features. Likewise, in the case of weld line defect prediction, the software must assume that the molten metal continuously flows throughout the casting even when two solidification fronts meet during the simulation. Therefore, weld lines never form during the simulation. Further discussion and evaluation of ProCAST’s ability to simulate the boundary layer is given in a subsequent section. The final conclusion from this study was that flow related defects are not accurately predicted but porosity, hot tear, and distortion defects are able to be simulated by ProCAST.

3.1.3.2. Solution Convergence

I also scrutinized solution convergence to test the effectiveness of ProCAST’s investment casting simulations. ProCAST has no built in functionality to clearly demonstrate that the flow, thermal, and stress equations are sufficiently converged by the solver algorithm. This is a weakness of the software.

In order to test for solution convergence, I monitored the deviation error between consecutive solver iterations for multiple turbine blade test cases. This was done in order to demonstrate that the solver would properly converge for a general turbine blade simulation study. In all simulations, the deviation error for each variable must approach zero in order to have proper solution convergence. If the deviation error of each variable does not approach zero, then the solution is invalid.

Figure 12 shows the deviation error for the x velocity variable of one of the turbine blade casting simulation test cases. The x velocity variable is the magnitude of the molten metal flow in the x direction. Each colored line in the graph represents a time step in the casting simulation. Each time step is a snapshot in time of what is occurring in the mold as the
metal flows, cools, and solidifies. For example, there could have been a time step at time 10 seconds. This time step is an estimate of what is occurring 10 seconds after the metal began to flow into the mold. The x axis in the graph describes the number of solver iterations needed to reach convergence. The y axis in the graph represents the deviation error between two successive solver iterations. In order to attain solution convergence, the deviation error of each time step must approach zero as the number of solver iterations increases. This is accomplished in the x velocity variable shown in the figure. For example, the time step represented by the white line tends toward zero as the number of solver iterations increases on the x axis. Similar graphs were also created and analyzed for the y velocity, z velocity, temperature, pressure, and stress solutions for the general test case. Solution convergence was also observed for each of these variables.

![Convergence: X Velocity](image)

**Figure 12:** Solution convergence of a turbine blade test case. Units in m/s.

I also performed another convergence test for the general turbine blade test case. ProCAST gives the user the ability to select a convergence criterion, the maximum deviation error where a solution is considered converged. Although the deviation error approaches zero, it never reaches zero. The convergence criterion tells the solver when the deviation error is sufficiently small to be considered converged.

Figure 13 shows the thermal contour plot of three turbine blade casting simulations where only the convergence criterion changed between each simulation. The first simulation used ProCAST’s default convergence criterion. The second simulation used a convergence
criterion that was half the default value. The third simulation used a convergence criterion that was a tenth of the default value. As can be seen in the figure, the thermal contour plots are practically the same. The temperature variable solution was unchanged regardless of the size of the convergence criterion. The same trend was observed in the flow and stress contour plots. In his academic work that describes the state of the art in casting simulation, Yu states "most of the simulation packages have default values set for the convergence criteria...the user is recommended to use these default values" (Yu, 2002, p. 48).

![Thermal contour plots used to test solution convergence. Units in °C.](image)

**Figure 13:** Thermal contour plots used to test solution convergence. Units in °C.

### 3.1.3.3. Mesh Density

I also analyzed the ProCAST software from a mesh density standpoint. The purpose of the mesh density evaluation was to make sure that an adequate average mesh size was chosen for the turbine blade casting simulations.

A test was performed in order to find a proper mesh density size for the general turbine blade test case. In the test, several mesh sizes were selected to represent a turbine blade. Specifically, average mesh sizes of 0.06 cm, 0.03 cm, and 0.01 cm were tested. The mesh...
size and thermal contour map for each mesh density are shown in Figure 14. Although the results look very similar, a close investigation shows a difference between the 0.06 cm simulation results and the 0.03 cm and 0.01 cm results. The 0.06 cm results contain much less information about the thermal contour map when compared to the 0.03 cm and 0.01 results. The 0.06 cm results are a much rougher estimate of the thermal contour map when compared to the 0.03 and 0.01 cm results. The 0.06 cm results simply contain less information than the other two results. In the case of 0.06 cm, the solver is unable to produce fine results because the nodes on the 0.06 cm mesh are spaced so far apart.

In addition to observing the thermal contour map, the flow and stress contour plots were examined. These contour plots produced the same conclusion as the thermal contour plots. The 0.03 cm average mesh size was shown to produce adequate results while minimizing the simulation time. In addition, the 0.03 cm mesh size also produced results that were precise enough to detect the three types of investment casting defects: porosity, hot tears, and distortion. Therefore an average mesh size of 0.03 cm was used to simulate all turbine blade castings.

Figure 14: Mesh and thermal plots used to test mesh size. Units in °C.

3.1.3.4. Boundary Layer

I also evaluated ProCAST's ability to simulate a fluid boundary layer, the layer of fluid closest to the mold wall. Boundary layer simulation is critical to properly simulating fluid flow in turbine blade castings. This fact was established by showing that the size of the
boundary layer makes up a significant portion of the total thickness within the casting. In order to establish this fact, a few calculations were made to determine the boundary layer thickness in the extremities of the casting. In order to calculate the boundary layer thickness, the Reynolds number was first calculated. The Reynolds number calculation showed that the flow within the casting was turbulent. The Reynolds number was then input into the turbulent boundary layer equation. This equation determined the boundary layer thickness. The boundary layer thickness was then compared to overall thickness of the casting in the extremities of the casting. For example, it was calculated that within the knife edges of a shrouded turbine blade the boundary layer made up about 40% of the total thickness of this portion of the casting. Because turbine blades are relatively small, it is important to be able to create a boundary layer in order to obtain a proper solution of the flow equations.

MeshCAST, the mesh generator built in the casting simulation software, has a feature that allows the user to create a boundary layer mesh. Although this feature was applied to several turbine blades to create a boundary layer mesh, MeshCAST was never able to generate a proper boundary layer mesh for any of the turbine blades. The mesh generator repeatedly created negative volumes that would crash the casting simulation solver. The boundary layer mesh generator was the limiting factor in predicting flow related defects in the simulations. Without a proper boundary layer mesh, the solver had to make simplifying assumptions that invalidated the flow related defect results obtained from the simulations studies.

3.1.3.5. **Solver Coupling**

The final criterion I used to evaluate ProCAST was solver coupling. Figure 15 describes how the software is set up to simulate the casting process. It can be seen in the graph that each solver is dependent on all of the other solvers to accurately simulate the casting solidification process. In fact, a test was performed to show that when any of the solvers were decoupled, the casting simulation could not be completed. For example, a turbine blade was simulated where the thermal solver was decoupled from the flow solver. Upon viewing the results, molten material flowed into the mold cavity but never solidified. In
this case, the flow results were not influenced by the thermal results. Similar results were obtained when the other solvers were decoupled.

![Figure 15: ProCAST solver coupling diagram.](image)

### 3.1.4. ProCAST Limitations and Approximations

As stated earlier, ProCAST casting simulation software has limitations. The limitations require that the output of the software must be considered an estimate of the casting process. The evaluation of the software determined that the prediction of flow related defects is a significant limitation of the software. Other limitations include boundary layer mesh generation and convergence monitoring.

### 3.1.5. ProCAST Evaluation

In a broad sense, I believe that ProCAST is a powerful casting simulation tool that needs further refinement for use in small engine turbine blade applications. In these applications, boundary layer effects have a significant influence on the fluid dynamics of the filling process. The software is best suited to simulate the casting of objects that are much larger than turbine blades. The software is limited by its ability to create and simulate a boundary layer in small castings. One of the most important defect types, no fill, cannot be properly simulated if a boundary layer cannot be properly created. This severely limits the applicability of the simulation software for small parts that have intricate features like outer shroud knife edges that are common to small turbine blade airfoils. On the contrary, large bulkier castings do not suffer from this limitation. The effects of the boundary layer are
much less significant in large castings. Therefore the ability to simulate a boundary is not a
constraint in a large casting. In summary, the accuracy of no fill related defect prediction is
better in larger castings compared to smaller castings. In addition, no fill defects are poorly
predicted by the simulation software. The accuracy of this type of defect prediction is
hindered by ProCAST’s inability to properly couple the thermal and flow solvers during
solidification modeling.

Other mechanisms for defect prediction in ProCAST need refinement. For example, hot tear
defect prediction in ProCAST is limited. At the present time, the output of the software is
simply a prediction on a relative scale. The output of the hot tear prediction model simply
reports which sections within the casting are more susceptible to hot tearing compared to
other sections of the casting. The output does not predict when hot tears begin to form. The
hot tear prediction model must be calibrated with a part that has actually suffered a hot tear
defect in order to determine a hot tear formation threshold.

The user interface in ProCAST also needs improvements. The way by which information is
input into the software is non intuitive in many cases. For example, material properties are
input into the software in two separate locations. The software will simulate the casting
process even when all the required material properties are not completely input into each of
the two locations. This problem could be easily remedied by combining the two input
locations and warning the user when the input is incomplete. Other similar user interface
issues include gravity vector input, heat emissivity input, and run parameter input. These
input options also suffer from similar issues like the material property input. The software
has limited functionality when the user is unable to properly input information that is needed
to simulate the casting process. If incomplete or incorrect is input into the software, the
simulation will be inaccurate.

Finally, the required calculation time of each casting simulation is limiting. The average
calculation time for many of the turbine blade simulations was over 24 hours even when flow
related defects were not predicted by using a boundary layer. The calculation time is limiting
because the user must spend too much time experimenting and adjusting the software before
the actual test case can be properly simulated. In addition, the simulation of large intricate castings is burdensome because the simulation takes weeks to complete.

### 3.1.6. Independent ProCAST Evaluation

When speaking of future developments of casting simulation software a number of years ago, one group of researchers said “while significant technical accomplishments have been achieved, much work needs to be accomplished” (Tu, Foran, & Hines, 1995, p. 65). This statement holds true today. The characterization has application to all casting simulation software, including ProCAST. ProCAST will never simulate the exact casting process but it will continue to be improved to provide engineers with better information about specific applications of the casting process.

Another group of researchers assessed ProCAST by stating “[ProCAST] laid down a foundation for improving...the castings” (Hu, Yang, Luo, Wang, & Chen, 2006, p. 293). ProCAST simulation results should not be used to describe everything that is happening during the investment casting process. The software serves as an approximation of the casting process and must be interpreted as such. ProCAST predicts trends not exact occurrences.

Others have given ProCAST a slightly better evaluation. One group of researchers stated “computer modeling with industrial and advanced solutions like ProCAST is an efficient way to improve product quality and process productivity” (Calba & Gaumann, 2006, p. 14). These researchers used the software to improve the casting process. In their study, they used the software to successfully investigate how to design the gates and vents of a specific casting application. It must be noted that these researchers investigated the ideal placement of large casting features and did not investigate small casting features like thin sections. As discussed previously, the simulation of these small sections is limited because a boundary layer mesh cannot be created in these small regions due to boundary layer grid problems.
3.2. Summary

Casting simulation software is used within the casting industry to simulate the casting process. ProCAST gives an estimate of the size and location of various types of defects like porosity, hot tear, and distortion. The software does not calculate exact occurrences. For example, prediction of flow related defects is limited because the software is unable to properly create a boundary layer mesh for small intricate features like knife edge seals on small turbine blades. The software is also limited by other factors like solution convergence monitoring, solver coupling, and user interface issues. Many independent researchers agree that the software is robust but still suffers from weaknesses. Further refinement of ProCAST is needed before the software can be used to reliably predict flow related defects on small turbine blades.

The final part of the paper will combine two design for manufacture tools, robust design and simulation software, and apply the tools to a specific turbine blade case. The specifics of the experiment like factor selection, experimental method, and experimental analysis will be outlined.
4. PART IV: Application of Methodology and Experiments

In this part of the paper, I describe how two design for manufacture tools, robust design and casting simulation software, were coupled on a specific turbine blade experiment. The experiment was designed to discover how turbine blade part features are related to investment casting defects. The results from the experiment are included in this part of the paper.

4.1. Robust Design of Experiments

Honeywell was one of the early adopters of six sigma, a quality management system. Honeywell saw value in the tool and employed it soon after Motorola introduced it in the late 1980's. Since that time, Honeywell has used this statistical based decision tool extensively throughout the entire company. The company claims to have saved billions of dollars from six sigma related activities. The robust design of experiments described in the following sections seeks to add to the cumulative saving that has already been realized by Honeywell. The experiment builds upon the tenants that Honeywell has already established.

4.1.1. Blade Selection

I first selected the turbine blade that would be used for the robust design of experiments. The selection process started with a few general criteria. The turbine blade had to have a manufacturing volume of greater than 1,000 parts per year, a significant manufacturing volume. Other early stage selection criteria included a blade whose design information was not export controlled by the United States government and a blade that had a complete CAD model.

After the initial screening was complete, I ran the remaining turbine blades through Honeywell’s turbine blade complexity model and design for manufacture scorecard. These two tools are used by Honeywell to gauge the degree of difficulty of casting a particular turbine blade design. The scores generated by the two tools help the design engineer quickly understand how readily the part can be manufactured based on the design features that have been selected for the turbine blade. The selected blade had to have a moderate complexity.
and design for manufacture score. The blade could not be overly complex because the simulation software might not be able to simulate the investment casting process of the complex design. In addition, the blade could not have an extremely low score because it had to have design features that were generic to many of Honeywell’s turbine blades.

After employing all of the selection criteria described above, I selected the blade that would be used in the simulated robust design of experiments. The selected blade can be seen in Figure 16. The selected shrouded turbine blade is made of a nickel based super alloy and is approximately the length of an adult human’s index finger.

Figure 16: The shrouded turbine blade selected for the simulated design of experiments.

4.1.2. Defect Survey

I then created a defect survey in order to make an informed selection of the control factors, noise factors, and performance metrics that would be used in the robust design of experiments. This defect survey was given to six of Honeywell’s investment casting experts that have spent significant time in investment casting foundries. Respondents to the survey were given a picture of a turbine blade and were asked to describe the locations on the turbine blade where defects were most likely to occur. Respondents were also asked to identify the defect type that often forms at each defect prone location. In addition, they were asked to identify the casting process parameters that had the greatest effect on investment casting quality. Respondents were also asked to rank the defect locations and the process parameters according to their relative importance. This information was then interpreted and
used to identify the control factors and noise factors used in the robust design of experiments. A cause and effect diagram based on the survey results is show in Figure 17.

![Figure 17: Manufacturing defect cause and effect diagram for turbine blades.](image)

**4.1.2.1. Control Factor Specification**

It must be noted that the control factors indentified in Figure 17 are all parameters that Honeywell can control in the turbine blade design. Several more potential control factors were identified but only the nine most important control factors are listed in the diagram. Although all nine are important indicators of the potential for casting defects, nine control factors was determined to be too many. The nine were pared down by calculating their relative importance to each other by utilizing the rankings that Honeywell’s experts indentified in the defect survey. In addition to this quantitative method, the relative importance of each of the nine was debated by Honeywell’s experts in a qualitative analysis. After evaluating the rankings and the outcome of the debate, I identified five control factors to be used in the robust design of experiments: blade length, section thickness, inside corner radius, root volume, and outside corner radius. These control factors are depicted in Figure 18.
I then selected two levels for each control factor. After consultation with Honeywell’s experts, the factor levels were selected. A high level, a dimension greater than the existing design, and a low level, a dimension that was less than the existing design, were used for each control factor. The experiment used a dimensional increase of approximately 15% for the high factor level and a dimensional decrease of approximately 15% was used for the low factor level.

4.1.2.2. Noise Factor Specification

The noise factors identified in Figure 17 are all factors that Honeywell is not able to control but still influence the quality of the investment cast turbine blade. Honeywell’s investment casting suppliers, Howmet and PCC, select these process parameters. In addition, these parameters are never exact because they have an associated tolerance band.

I used a quantitative and qualitative analysis to indentify the noise factors that would be used in the robust design of experiments. After the rankings were used to gauge the relative importance of the control factors, I employed the help of Honeywell’s experts to determine the final noise factors. The nine potential noise factors were pared down to two: mold temperature and fill time. The noise factors were used as compounded noise. When compounding the noise in a robust design of experiments, the two noise factors are combined to represent extremes in the noise conditions. Each experiment is run twice, once at the low noise factor settings and once at the high noise factor settings. The range
of the two experimental results is used to describe the robustness of the control factors to the noise factors. The high noise factor level was the average mold temperature and average fill time. The low noise factor level was the lowest mold temperature in the range and the lowest fill time in the range.

4.1.2.3. **Performance Metric Specification**

I then selected three performance metrics for the design of experiments: porosity, hot tear, and distortion. The defect survey, investment casting texts, and the capability of ProCAST dictated which performance metrics would ultimately be measured by experiment. The defect survey and investment casting texts identified the types of defects that could form during the casting process and ProCAST dictated those that could be measured by the experiment. The simulation software was the limiting factor. As stated previously, many defect types were identified but only three could be reliably simulated by ProCAST.

Once the defects were identified, the output of ProCAST had to be transformed to create a metric that could be measured. The method used to transform the ProCAST output for each of the three defect types was different. In the case of porosity, the volume of porosity that ProCAST predicted could be changed by selecting different porosity cutoff percentages. The user is able to indicate the cutoff point where porosity will begin to be measured. Many of Honeywell’s turbine blade specifications state that any given volume that is greater than 2% porous, less than 98% dense, will be considered porosity defective. I decided that the experiment would err on the side of caution so a porosity cutoff of 1.5% was selected. The total volume of porosity within the turbine blade was measured at this cutoff percentage. Cubic centimeters were used as the unit of measurement for porosity.

The interpretation of the hot tear metric was slightly more complicated. As described previously, the software outputs a relative indication of hot tearing, not a prediction of whether or not hot tearing will occur. In other words, the hot tear contour plot simply tells the user which parts of the casting are more or less likely to experience a hot tear. The software must be calibrated by the user in order to establish a cutoff point where the hot tearing indicator begins to predict a defect. In order to calibrate the hot tear indicator, I
selected a part with known hot tear issues and compared this information to the part’s hot
tear simulation from ProCAST. The locations on the part that frequently experienced
known hot tears were used as an indication of when hot tears would begin to form on the
part. The magnitude of hot tear indication was noted at these points on the part. Any
magnitude greater than or equal to the calibrated magnitude was considered as a hot tear.
After calibrating the indicator, each area of the casting that showed signs of hot tearing was
measured to determine a dimension of hot tearing. I interpreted this dimension as the total
hot tear crack length. The sum total of all critical locations on the casting that showed hot
tearing was used as the hot tearing metric. Centimeters were used as the unit of
measurement for the hot tear metric.

The interpretation of the distortion metric was less complicated than the hot tear and
porosity metrics. The distortion contour map that ProCAST outputs was simply interpreted
as the total distortion within the casting. Like the hot tear metric, the distortion metric
identified several critical locations. Distortion measurements were taken at the critical
locations in the casting and weighted according to their relative importance. A sum total of
all the weighted distortion measurements was used as the final distortion metric. Once
again, centimeters was used as the unit of measurement for the distortion metric.

I used a minimizing objective function for the three metrics. In all three cases of defects,
less is better. Minimizing the volume of porosity, the linear dimension of hot tearing, and
the linear dimension of distortion improves the quality of the casting.

4.1.3. Design of Experiments Setup

I utilized an orthogonal array experimental design setup. I choose this setup because it is the
most efficient experimental setup. It uses a minimum amount of experimental runs to
ascertain the main effects of all of the control factors. In addition, the setup allows for
testing of a few interaction effects between the control factors.

Specifically, I choose an L8 orthogonal array for the experiment. The experimental setup can
be seen in Table 5. A total of sixteen runs were performed in the experiment. Each row was
run twice, once at a low noise factor setting and once at a high noise factor setting. As can be seen in the table, each of the sixteen experiments produced a porosity, hot tear, and displacement result.

<table>
<thead>
<tr>
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<th>porosity result (cc)</th>
<th>hot tear result (cm)</th>
<th>displacement result (cm)</th>
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<td>1</td>
<td>N-</td>
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</tr>
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</tr>
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</tr>
<tr>
<td>7</td>
<td>outcorner</td>
<td>1</td>
<td>N-</td>
</tr>
</tbody>
</table>

Table 5: L8 experimental design used in the simulated robust design of experiments.

As described previously, the experiment was set up to test five control factors and two noise factors in the experiment. The five control factors made up columns 1, 2, 4, 6, and 7 in Table 5. The high and low noise factors can be seen in each of the defect results columns in Table 5. Although the L8 array allows the experimenter to test seven control factors, only five control factors were selected for use in the experiment. Columns 3 and 5 were left blank in order to test the interaction effects between a few of the control factors. Specifically, this experimental design allows for testing interaction effects between columns 1 and 2, blade length and section thickness, and columns 1 and 4, blade length and inside corner radius. This setup that allows for testing of the described interaction was proposed by a robust design expert (Ross, 1998).

4.1.4. Experimental Runs Description

I simulated each experiment in ProCAST. The average setup time for each of the runs was approximately 4 hours. The setup process included creating a unique CAD model for each of the experimental runs, building a FEA mesh of each unique CAD model, and assigning initial conditions to the model. The investment casting simulation was performed after all the runs were properly setup. Each experimental run took approximately 22 hours to simulate. In total, each run took slightly over 26 hours to set up and complete.
4.1.5. Experimental Results Description

The results from the sixteen experimental runs in the simulated robust design of experiments can be seen in Table 6. Note that each run was performed twice, once at a low noise factor setting and once at a high noise factor setting. Each of the sixteen runs produced a porosity, hot tear and displacement result.

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<th>hot tear result (cm)</th>
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Table 6: Results of the simulated robust design of experiments.

4.1.6. Analysis of Experiments

I used the results of the experiment shown in Figure 6 to calculate an average and range of each run. Table 7 presents the data from these calculations. For example, Table 6 shows that the porosity result from run number 1 was 0.040 for the low noise setting and 0.110 for the high noise setting. The average of these two results is 0.075 and the range caused by the change in the noise factor level is 0.070. These values can be seen in Table 7. I used the average result to determine the main effect of each control factor and the range result to measure the robustness of each control factor.

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Table 7: Average and range results of the simulated robust design of experiments.
4.1.6.1. **Main Effects Analysis**

I used the main effects of the control factors to perform an analysis of means. This analysis revealed which of the five control factors were most influential in effecting porosity, hot tear, and distortion defects in the turbine blade. The analysis was also used to determine the factor settings that minimize the effect of each type of defect. In the analysis, each defect result is averaged at the low factor level and high factor level. These results are then plotted to determine the optimal control factor settings.

For example, it can be seen in Table 7 that the section thickness was at the low factor level for runs 1, 2, 5, and 6. The porosity result for each of the runs was respectively 0.075, 0.070, 0.040, and 0.096. Therefore, the average low section thickness result for porosity was 0.070. In addition, the section thickness was at the high factor level for runs 3, 4, 7, and 8. The porosity result for each of these runs was respectively 0.125, 0.150, 0.190, and 0.175. Therefore, the average high section thickness result for porosity was 0.160. The section thickness results for porosity and the other control factors can be seen in Figure 19.

![Average Porosity](image)

**Figure 19:** Average porosity result for the 5 control factors. Units in cc.

The graph in Figure 19 shows that the section thickness control factor has the greatest effect on porosity in the casting. The range of this line, the pink line in the graph, is the greatest. In addition, porosity will be minimized by setting all of the control factors to low
except for the outside corner radius. Similar graphs for hot tear and displacement are shown in Figures 20 and 21.

![Average Hot Tear Graph](image)

**Figure 20:** Average hot tear result for the 5 control factors. Units in cm.

Like the porosity graph, the hot tear graph in Figure 20 shows that the section thickness control factor has the greatest effect on hot tearing in the casting. Hot tearing is minimized by setting the blade length, root volume, and outside corner radius to low. In addition, section thickness and inside corner radius should be set to high to minimize hot tearing.

![Average Displacement Graph](image)

**Figure 21:** Average displacement result for the 5 control factors. Units in cm.

The displacement graph in Figure 21 shows that the blade length has the greatest effect on displacement defects in the casting. Displacement defects are minimized by setting blade length and root volume to low. All other control factors should be set to high to minimize displacement defects.
The graphs in Figures 19 through 21 must be collectively compared and contrasted in order to determine the control factor settings that minimize all three defect types. Blade length and root volume always minimize defects when they are set to low. Likewise, outside corner radius always minimizes defects when it is set to high. Although the setting for inside corner radius cannot be definitively determined, this factor has little effect on the three defects relative to the other control factors. In contrast, the optimal setting for the section thickness control factor cannot be definitively determined. The section thickness setting has the most significant effect on two of the three defects. There exists a significant tradeoff between minimizing the porosity and hot tear defects when selecting a setting for the section thickness.

4.1.6.2. Robustness Analysis

I also performed an analysis of robustness on the control factors. The analysis was used to determine the control factor settings that minimize the effect of the noise factors. In the analysis, I calculated an average range between the low noise result and the high noise result for each control factor setting. The average range is then used to gauge the robustness of each control factor setting. If the range is small, the setting is considered robust. If the range is large, the setting is considered less robust.

For example, Table 7 shows that the root volume was at the low factor setting for runs 1, 4, 5, and 8. The porosity range caused by the low and high noise settings was respectively 0.070, 0.020, 0.020, and 0.010. Therefore, the average porosity range when the root volume was set to low was 0.030. The root volume was set to high in runs 2, 3, 6, and 7. The porosity range was respectively 0.040, 0.050, 0.050, and 0.060 in these runs. Therefore, the average porosity range at the high root volume setting was 0.050. The porosity results for root volume and the other control factors can be seen in Figure 22.
Figure 22: Porosity range result for the 5 control factors. Units in cc.

Figure 22 is used to determine the control factor settings that are most robust to the noise factors with respect to porosity. The graph shows that in order to minimize the effects of the noise factors, all control factors should be set to high except for root volume. In addition, it must be noted that these setting are only moderately robust to the noise factors because the range is a significant percentage of the average response. This can be shown by comparing the y axis is Figure 19 to the y axis in Figure 22. The range is approximately 33% of the average response and therefore the optimal settings described above are only moderately robust to the noise factors.

Figure 23: Hot tear range result for the 5 control factors. Units in cm.

Figure 23 represents the range created by the noise factors with respect to hot tearing. Like the porosity settings, the robust hot tear settings are all high except for blade length and outside corner radius. Even though these setting are optimal, none of the setting are truly
robust. It can be seen that the range makes up about 100% of the average response when comparing the y axis of Figures 20 and 23.

Figure 24: Displacement range result for the 5 control factors. Units in cm.

Figure 24, which describes the robustness with respect to displacement defects, is interpreted in the same way as the other range graphs. When selecting robust settings with respect to displacement defects, all factors should be set to low except for the root volume. The displacement settings are perhaps the most robust because their range is about 10% of the average response. This can be seen when comparing the y axis in Figures 21 and 24.

Finally, when Figures 22 through 24 are compared simultaneously, it can be seen that there exist many tradeoffs in selecting the control factor settings that are most robust. In addition, there are even greater tradeoffs when comparing Figures 19 through 24 to select the globally optimal performance and robust control factor settings.

4.1.6.3. Interaction Analysis

The final analysis I performed in the robust design of experiments was an interaction analysis between a few of the control factors previously specified. The interaction between blade length and section thickness was tested and the interaction between blade length and inside corner radius was also tested. These specific interactions were identified as key interactions that needed to be tested when the robust design of experiments was set up.
After I performed the analysis, only two interactions were found to be significant. The interaction between blade length and section thickness was found to be significant for both the porosity results and the hot tear results. The interaction plots for these defect types are shown in Figure 25.

![Interaction plots for blade length and section thickness. Units in cm.](image)

**Figure 25**: Interaction plots for blade length and section thickness. Units in cm.

### 4.1.7. Additional Experimentation

Upon reflecting upon the experiments, I believe additional experimentation is warranted. The inside corner radius, outside corner radius, and root volume were never significant factors in effecting any of the defects. These control factors should be eliminated and replaced with other control factors that would potentially be more influential. Examples of the other potential control factors can be seen in Figure 17. Other significant noise factors should also be inserted into the experiment. These other influential noise factors could potentially include pour temperature or gating scheme.

Experimentation beyond the experiment outlined in this part of the paper would be able to confirm the control factor set points from the first experiment. In addition, extra experiments would be able to test other interactions that are potentially significant and confirm that some additional interactions are not significant.
4.2. Summary

In this part of the paper I described a specific experiment where casting simulation software and robust design were coupled for experimental purposes. I used a robust design experimental process to set up, run, and analyze the experiment. In the final analysis of the experiment, I found that the section thickness and blade length of the turbine blade were significant drivers of investment casting defects.

The final part of the paper will establish a number of conclusions from the research project. In addition, I propose a direction for future research on the subject.
5. PART V: Conclusion

I described a methodology to improve the manufacturing yield of investment cast turbine blades in the previous four sections of this paper. The methodology employed two design for manufacture tools: robust design and casting simulation software. The first section of the paper first outlined the problem of defects in investment cast turbine blades. The second section then described how robust design has been used previously to address similar problems. Sections three and four then described the specific tools that were used to address the problem.

5.1. Conclusions and Recommendations

Four conclusions and recommendations can be drawn from the research project. First, it is in the best interest of aerospace companies to put processes in place that will allow the companies to garner defect data from their turbine blade suppliers. This data is an essential to improving the manufacturability and cost of the turbine blades that are outsourced to the suppliers. As described in this paper, the process will have to first identify the incentives to which the suppliers will respond. After identifying the incentives, mechanisms in the form of formal contracts can be put in place to ensure the defect data are shared.

Second, the robust design of experiments described in this paper identified a few levers that can be used to decrease the number of porosity, hot tear, and displacement defects that are found in an investment cast turbine blade. The levers should be used to increase the manufacturability of future turbine blade designs that are similar to the turbine blade described in the experiment. In addition, the robust design of experiments method should be used in the detail design phase to increase the manufacturability of the turbine blades. This method will anticipate future manufacturing problems by identifying problems up front. By identifying problems early in the design process, the cost of the turbine blades will be driven down.

Third, it should be noted that the methods described in this paper are widely applicable to other cast components. For example, similar experimentation can be done on cast gear housings, cast electrical housings, other cast turbine blades, and other cast components. The
simulated experimentation will identify problem areas in these castings without requiring costly experimentation. The experimentation will also identify other levers that can be manipulated to decrease the number of defects found in the particular casting.

Finally, it must be recognized that manufacturing simulation software must be carefully examined to determine its strengths and weaknesses. Too many software packages over promise and under deliver. Trial versions of manufacturing simulation software should be used to carefully scrutinize the capabilities and shortcomings of the software before it is fully implemented.

5.2. Future Research

Future research efforts should be focused on how aerospace companies can use the robust design process to improve other parts on the jet engine. These parts could be mechanical or electrical in nature. As was shown in this paper, the robust design technique is a very powerful tool that can be used to improve any design. The technique is able to identify the significant variables that influence the manufacturability of any component. These variables can then be set to maximize the performance of the component even when noise is present. The design of the components that have been subjected to robust design will be improved.

Future research should also revolve around how to use investment casting defect data to create other design for manufacture tools. After a system is put in place to regularly gather defect data, the tools can be built. The tools could come in the form of statistically based yield prediction models or expert systems that guide design engineers in creating designs that are more readily manufactured. The defect data is a valuable source of information that will allow aerospace companies to build design for manufacture tools for investment cast turbine blades. These tools will help guide design decisions to minimize the likelihood of manufacturing defects.

In addition, future research should be done to validate casting simulation software with real casting data. This research would compare casting simulation studies with actual casting studies where molten metal is poured. Many companies in the turbine blade casting industry
would benefit from this study. Because of the cost of the study, a consortium of foundries, companies, and universities would need to be formed to fund the study. The knowledge garnered from this study would then be disseminated to all of the entities that funded the research.
Bibliography


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