

INTRODUCTION

In this fast paced world of ours, it seems everyone is trying to get “there” more quickly. Board a plane instead of a bus. Send E-mail instead of a letter. No matter what the technology, the pace just gets faster and faster.

The same situation exists in the injection molding industry. Increasing customer demands are really “turning up the heat” on injection molders. Customers are demanding that injection molders get “there” more quickly. Customers are demanding tighter tolerances, lower costs and shortened development times. As a response to this increased “heat,” many injection molders find themselves in constant “fire-fighting” mode. As one injection molder stated, “You think the pressure in the mold is high, sometimes the pressure on the engineers in this industry is overwhelming.”

As a result of this increasing pressure, a revolution is taking place in the injection molding industry. Clearly, injection molders want to meet customer demands AND make money. There is an **easy** technique injection molders can use that takes them out of fire-fighting mode and allows them to not only remain competitive, but also increase their profits.

No matter which plastics process is your speciality, design of experiments can help make it more efficient and productive.

Experimental design was first developed in England during the early 1900's. A statistician (and agricultural scientist) named Ronald Fisher is credited by many with some of the first applications of the tool as well as developing much of the fundamental mathematical theory underlying statistical experimental design. Injection molders are now learning that experimental design applied in conjunction with ample knowledge of molding processes can be an efficient characterization, optimization, and set-up strategy.

"Change only one variable at a time" was once a common theme in injection molding. Thanks to Experimental Design, all has changed. Experimental Design is a powerful set-up and troubleshooting tool for the injection molder. With this tool, the user conducts a family of tests, making multiple simultaneous changes in variable settings. Analysis techniques (using software) have recently emerged which allow the user to quickly characterize and determine the best settings for the process. Use of Experimental Design was once reserved for only those with a specialized knowledge of mathematics and statistics (being able to interpret an ANOVA table is not an innate skill for the injection molder!). Today computer software makes analysis and optimization easy. All one really needs to be able to do is operate in the Windows™ environment and to interpret a few graphs. Instead of spending days attempting to set up a new job or troubleshooting a problem, molders have frequently found they can get a solution in a

matter of hours.

Successful application of design of experiments involves the blending of several skills. Foremost among these skills is knowledge of the technology of injection molding. Fortunately, often the process experts in injection molding know what the three or four most important variables are likely to be and what the appropriate ranges are for these variables. What they likely do not know, however, is the best settings for these key variables in order to get desirable results for more than one quality characteristic (response). Without some knowledge of what the key variables are and what the likely best range of settings is, the molder will have little success with the technique. In addition to technical knowledge, team planning, communication, DOE software, and Windows™ skills are also important. There are a number of DOE software packages in the marketplace. One the authors prefer, because of its ease-of-use and power, is a package called *DOE Wisdom*.

Essential to the successful use of experimental design by the molder is the recognition that injection molding is controlled by the fundamentals of science. Although it might appear at times that no matter how many controls are in place, the plastic is going “to do as it darn well pleases,” there is a scientific reason for all that takes place in the molding of a part. Practitioners need to look at the challenge of setting up a job from the perspective of plastics science.

The concept of Decoupled MoldingSM (Scientific Molding) has generated significant interest in the injection molding community over the last several years. Proponents of this approach have documented substantial improvements using these techniques (citation: *Injection Molding* magazine, 55 Madison St., Suite 770, Denver, CO 80206). The concepts of Scientific Molding certainly make a great deal of sense. Some of the basic premises are:

- The focus of molding is the performance of the polymer in the mold.
- One should think about what is happening from the plastics standpoint.
- Scientific molding is a machine-independent process (make job set-up robust).
- One should develop a universal set-up card for each material/mold.
- Molding is not a "black art"; there is a logical reason for everything that happens.

Implementation of scientific molding, particularly for a small custom molding shop, may appear at first to be cost prohibitive. Pressure sensors must be placed in the mold. Sensors need to be positioned in the *right* place. Data collection and timely reaction systems need to be implemented. Fortunately, using design of experiments to set up and troubleshoot your process is a viable option. Additionally, studies by experts in the field vividly demonstrate that inserting pressure sensors in a mold more than pays for itself over the life of the job (citation: RJG Associates, Traverse City, MI 616-947-3111). The

combination of design of experiments and the use of pressure sensors in the cavities of long running molds is the ideal approach and (for most molders) is not cost prohibitive.

There are five stages that the injection molder must go through in order to successfully apply experimental design. They are:

- Planning
- Selecting an Orthogonal Array (family of tests)
- Conducting the Experiment
- Performing the Analysis
- Confirming the Results

To be successful at the first stage, *planning*, a team must know :

- Customer Requirements
- Company Goals
- Technology (machines, molds, characteristics of the resin, etc.)
- Team Skills
- Facilitation Skills
- Communication Skills
- Resources/time availability of machines and people

The second activity, *selecting an orthogonal array*, was once shrouded in a high degree of statistical mysticism. In the recent past, if an engineer or technician wanted to conduct a designed experiment, he/she would select possible factors and levels and pay a visit to the local statistical wizard. The engineer or technician would hand off the pertinent information and leave abruptly as the statistician grumbled to come back in a couple of days. The statistician would lay out an intricate fractional factorial design. A couple of days later, the engineer would return to accept the worksheet, having no idea how the runs were generated.

Times have changed. Designs no longer need to be generated manually. Tabled orthogonal arrays and easy-to-use software provide the molder with tools to fit his/her needs.

The third stage, *conducting an experiment*, requires a detailed plan, discipline in following the plan, and an understanding of what the experiment is intended to accomplish. Many texts on experimental design give little or no information about this stage. Therefore, this is one of the biggest reasons why people get poor results from an experiment. Those involved must realize that the only changes to be made are those called out by the orthogonal array. All other potential sources of variation must be held constant, or as close to constant as possible.

Analyzing data is still seen by some, unfortunately, as what experimental design is all about. For example, many courses and texts on experimental design may spend as much as 80 to 90 percent of their attention on this area. Analysis of variance and regression

typically are touted as the techniques of choice. Recent revelations have shown that by using simple graphs only, we can obtain a solid understanding of the results of a designed experiment. Analysis of Variance and regression output tables generated by the computer can, of course, provide additional information from the data.

The last stage, *confirmation and conclusions*, is the true test. As the name implies, we take the predicted best settings from the analysis stage and run those combinations with 20 to 30 shots, depending on the budget. If the results of the confirmation match the predicted values, all goes well. The experiment has confirmed. If not, this shows that one or more of our assumptions is invalid. Failure to confirm directs us to look for and find reasons for the unpredictable behavior before starting more experiments. (**Note:** Successful confirmation does not necessarily imply process capability. Determining process capability requires a much more detailed study. For more information on process capability studies, the authors recommend the *Statistical Process Control (SPC) Reference Manual* which can be obtained from the Automotive Industry Action Group. (248-358-3570))

Getting good at the application of this approach takes practice. Too often, people will try experimental design once, find the approach felt awkward, and not try it again. We like to stress to people the "510" rule. One needs to participate in at least 5 experiments to understand what the techniques can do. (Completing 10 makes one really good at the technique.) "Getting good" does involve making an investment. The payback, however, will be huge. Molders typically see a 50 percent (or more) improvement in the efficiency and effectiveness of their setup and optimization efforts once they become skillful.

Experimental Design is a powerful tool for the setup and troubleshooting of injection molding processes. It requires a number of important skills including solid technical knowledge of the process. Thanks to the availability of powerful computers and graphical output from easy-to-use software, the injection molder can quickly combine his/her injection molding knowledge with simple experimental design for quick solutions.

Preface

Being successful as an injection molder was once a simple proposition. Line up some capital, hire a few key people with some knowledge of injection molding, link up with a couple of customers, and start making money.

Times have changed. Customers are becoming much more demanding. Margins are now smaller. Machines are more complex. New and exotic resins are being used to meet wider usage environments. Competition is now on a world-wide basis. The auto industry will charge you for their downtime if your component shuts down their line. Medical device customers (at the urging of the FDA) are demanding that you validate your processes. Customers (especially in the auto industry and medical device industry) are recommending molders use tools like experimental design to characterize and further the understanding of their processes.

Some advocates of experimental design suggest that all you need is designed experiments. No knowledge of injection molding is required. We disagree with this statement. Blending a fundamental knowledge of experimental design with ample knowledge of machines and materials is the key to successful application for the injection molder. By wisely combining experimental design with knowledge of the technology, you can continuously improve your understanding of designed experiments and injection molding technology.

Unfortunately, design of experiments (DOE) has gotten a bad reputation as being a complex and confusing topic. The authors aim to change this perception. Our approach is to make design of experiments easily understood and helpful to the injection molder. The first chapters of this book walk you through the basics of experimental design. Simple analysis techniques are discussed as they relate to the injection molding industry.

Thanks to the power of readily available software, it is easy to apply design of experiments to injection molding processes. This book includes a special version of *DOE Wisdom* software. Chapter 6 actually walks the reader through an injection molding example using the software.

Later chapters of the book are intended to discuss more advanced experimental design topics and to describe how DOE can help you meet some of the unique requirements of the plastics industry. For those readers who want to dive into more complicated mathematical concepts, Appendix A has been included.

It is our hope that this book will take the mystery out of experimental design. It does not

have to be complicated and confusing. For the most part, simple mathematics can be used. Real world injection molding examples have been used extensively throughout this book to help molders better understand how DOE applies to their industry and how it can be used to help them better compete on a world-wide basis!

NOTE: Our mission is to continuously improve this text. With your help we can meet this goal. If you see a typographical error, sentence structure or technological error, please bring it to our attention. You can reach us at 719-282-1143 or e-mail us at Launsby@aol.com.

Table of Contents

Introduction

1

Chapter 1: Design of Experiments - The Simple Facts

The Real World	5
When to Apply Design of Experiments	5
What is a Designed Experiment?	6
What is a Process Diagram?	6
What is a Factor?	6
What is a Response?	7
Planning Your Experiment	8
A Process Diagram for an Injection Molding Experiment	9
An Orthogonal Array	10
Let's Collect Some Data	13
The Pareto Chart	14
The Main Effects Plot	15
The Contour Plot	17
Summary	18

Chapter 2: Fractional Factorial Designs

You Can't Get Something for Nothing	21
What is an Interaction?	21
Aliasing	22
Resolution	25
Process Diagram for Fractional Factorial Design	25
The Worksheet	27
Potential Pitfalls of Data Collection	27
The Pareto Chart	29
Statistical Analysis	30
Terminology	30
Key Information	33
The Main Effects Plot	34

Confirmation Runs	35
Summary	36
Chapter 3: Optimizing More Than One Response	
What if I have multiple responses I want to optimize?	39
Desirability Functions	39
Desirability Function Example	40
Background	40
Experiment Objective	41
Factor Settings and Design Matrix	41
Responses	42
Data	42
Main Effects Plot	42
Software	44
Response Surface Graph	45
Contour Plot	45
Experiment Conclusion	47
Confirmation Runs	48
Desirability Function Summary	48
Chapter 4: Other Design Types	
Introduction	51
Plackett-Burman Designs	51
Taguchi Designs	51
Taguchi Example	60
Background	60
Experiment Objective	60
Factor Settings and Design Matrix	61
Responses	62
Analysis	62
Conclusion	66
Confirmation	66
Taguchi Signal-to-Noise Ratio	66
Smaller is Better	66
Larger is Better	66
Nominal is Better	67
Taguchi Summary	67
Modeling Designs	68
Box-Behnken Designs	68
Central Composite Designs	69
D-optimal Designs	70
Summary	71

Chapter 5: Hitting the Target - Sometimes It's Not Enough	
In An Ideal World	75
An Injection Molding Example - Reducing Variation	76
Factor Settings and Design Matrix	76
Response	76
Data	77
Main Effects Plot	77
Hit a Target	78
Hit a Target Confirmation	78
Reducing Variation	79
Hit a Target AND Reduce Variation Confirmation	81
Summary	81
Chapter 6: Using DOE Software	
The Importance of Software	85
Installing <i>DOE Wisdom</i>	85
Project Window	85
Design Definition	87
Adding Factors	87
Defining the Responses	89
Design Type	91
Base Runs/Resolution/Total Runs/Centerpoints	91
Order	92
Accepting the Defined Design	92
Generating a Worksheet	92
Data Definition Window	93
Statistics	94
Analysis of Means	94
Analysis of Variance	96
Prediction Equation	97
Hitting a Target	99
Graphics	101
Pareto Chart	101
Scatter Plot	103
Main Effects	104
Contour Plot	105
Response Surface Plot	106
Software Summary	106
Chapter 7: ISO 9000, Six Sigma, The FDA and Other Great Mysteries	
The Times They Are A Changing	109

Six Sigma Review	110
How Design of Experiments Can Help with Six Sigma	110
ISO 9000 Review	111
How Design of Experiments Can Help with ISO 9000	111
The FDA - Process Validation	114
How DOE Can Help with Process Validation	115
Summary	119
Chapter 8: The World of Plastics	
Introduction	123
Key Concepts	123
Viscosity	123
Fountain Flow	125
Cavity Pressure Gradients	128
Resin Type Impacts on Shrinkage	131
Summary	132
Chapter 9: Case Studies	
Taguchi L ₈ - Printer Part Material Evaluation	135
Box-Behnken Design - Bearing Component	142
¼ Fractional Factorial Molding Experiment	149
Full Factorial - Connector O-ring Diameter Evaluation	157
Appendix A	163
Index	

CHAPTER 1

Design of Experiments - The Simple Facts

The Real World

In the early and mid 70's the injection molding world was more stable. Foreign competition was minimal. Unlike today, complacency reigned in the marketplace; after all, inefficiencies could always be passed on to the customer.

This "business as usual" mind set received a severe jolt in the late 70's and early 80's. American industry awoke to the fact that they were faced with tough worldwide competition. Higher quality and lower costs were attracting U.S. consumers to foreign produced products. Cost and quality had replaced complacency as the predominate features of the market place.

By the 1990's, a third consideration had joined quality and cost issues in assuming dynamic significance on the global stage - the time-to-market factor. No longer could

leading companies retain drawn-out development and design cycles and hope to remain competitive. Businesses which prioritized quick response time across their organization consistently outperformed their slower competitors in terms of growth and profitability [1].

Everywhere, the lament of management is the same:

“In contrast to only five years ago, we must now develop new products in half the time (or less!), the job must be done with fewer people, and the product must be right with the first shipment.”

Obviously, traditional approaches are no longer adequate in meeting the challenge. In response to widespread demand, experimental design has emerged as THE premier tool in allowing technical groups to make faster, more informed decisions about product concepts, designs, and processes. Properly applied, companies realize a 50% - or greater - improvement in their efficiency and effectiveness.

When to Apply Design of Experiments

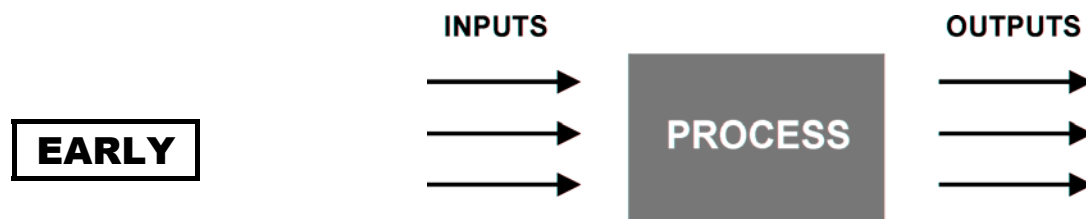
- Don't wait until the manufacturing phase of the new product.
- Design of Experiments is an effective tool to use in the R&D, Product Design and Process Design phases.
 - Use when setting up new molds and troubleshooting problem jobs.

What is a Designed Experiment?

A designed experiment involves systematic, controlled changes of the Inputs (factors) to a process in order to observe corresponding changes in the Outputs (responses). A designed experiment is an observation process where tests are conducted in a rigorous, systematic manner. For each test, important outputs are measured. Analysis of the resultant data is used to characterize, optimize, or troubleshoot an injection molding process.

What is a Process Diagram?

A Process Diagram is a graphic which assists in planning a designed experiment. Pictorially, it is as follows:



As shown above, the Process Diagram allows us to list inputs and outputs for the process. Selecting the correct inputs and outputs to study in a designed experiment (DOE) requires knowledge of what you wish to improve as well as strong knowledge of the technology of injection molding [2,3,4,5]. In a typical injection molding scenario, the molder might choose to call the inputs process parameters and the outputs the customer requirements. In DOE, the inputs are frequently referred to as **factors** and the outputs are referred to as **responses**.

What is a Factor?

In a designed experiment we want to select inputs (factors) that we can purposefully change in order to observe the corresponding changes in the outputs (responses). Some potential factors for an injection molding process might be:

Material Type	Material Variation	Screw RPM
Regrind %	Moisture Content	Injection Pressure
Pellet Geometry	Barrel Temperature	Injection Time
Pack Pressure	Pack Time	Hold Pressure *
Hold Time	Cooling Time	Cavity Number
Tool Temperature *	Cavity Pressure *	Melt Temperature *
Injection Speed *		

(*) Frequently the key factors to study

Control factors are factors that can be controlled. For example, the injection molder can control the hold pressure. These are the factors we believe will influence our responses. We want to vary these factors systematically. We will look at these factors at different levels (at least two levels) and understand their influence on our responses.

A **noise factor** is any factor which is known (or believed) to affect our response, but we either cannot, or choose not, to control. Room temperature might be an example of a noise factor. Viscosity change due to resin lot, moisture, or percent regrind is another example. You “might” be able to control it but you choose not to control it during the experiment. Not every experiment will have noise factors. Only when we want to be “robust” or “rugged” to a certain factor will we include it as a noise factor.

Constant factors are factors we do not want to study. Either we already know what their best settings are or we don’t believe they will influence our responses.

Quantitative factors are those whose levels can vary over a continuous numerical scale. Time, temperature, and pressure are examples of quantitative factors.

Qualitative factors have discrete levels. Qualitative factor levels cannot be arranged in order of magnitude. Material type would be an example of a qualitative factor.

What is a Response?

Selecting the appropriate response or quality characteristic to measure is critical to successful experimentation. Your experiment will be driven by the process output (response) that you choose to observe. Of course, meaningful and measurable responses will help us have a more successful experiment. Some potential responses for an injection molding process might be:

Dimensions	Color
	Bowing
Cavity Pressure	Tensile Strength
	Specks
Blisters	Blush
	Sink
Flash	Marks
	Delamination
	Knit
Weight	Lines

It is preferable to select a response that is measurable on a continuous basis. The dimension of the part is an example of this type of response. Categorical responses such as “pass/fail” require much larger sample sizes. Many injection molders have responses that are based upon a visual examination. If you are measuring sink marks, you should try to have more than just “pass/fail” criteria. It is better to set up a scale from 1 to 5 and rank the number of sink marks based upon this criteria.

Planning Your Experiment

Experimental design does not replace your engineering knowledge. As a matter of fact, you are counting on that knowledge to help you select the proper factors, factor levels and responses. You should sit down with the appropriate people and brainstorm what response(s) you want to optimize. Before you set up a designed experiment, list what you already know about your process.

Before selecting a response, make sure your measurement system is reliable. We have seen too many otherwise well conceived experiments decimated by measurement systems which were not reliable. Let’s say you want to optimize the dimension of your product with the following specification limits:

Minimum = 2.367 inches Nominal = 2.375 inches Maximum = 2.383 inches

A measurement repeatability study on your equipment shows that it can only

discriminate to +/-0.1 inches. The same part measured three times on this equipment gives the following readings:

2.4 inches 2.3 inches 2.5 inches

Clearly this measurement equipment would not be adequate to use for your experiment. No matter how well you conduct your designed experiment, the results will be erratic if your measurement system is not repeatable and reliable. The *Statistical Process Control (SPC) Reference Manual* gives an excellent explanation of how to evaluate your measurement equipment [6].

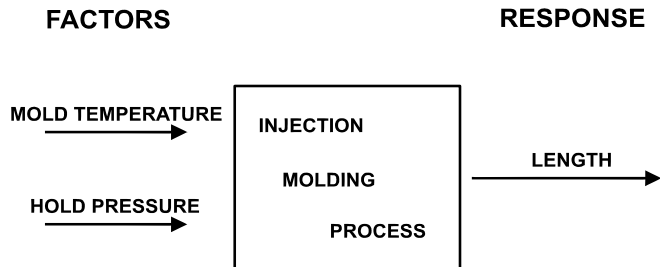
Once you have chosen the response(s) you would like to optimize and have determined that the measurement devices are repeatable and reliable, you must now choose your factors for the experiment. Here is where your engineering knowledge really comes into play. An injection molding process has *many* potential factors. We have heard of molders attempting to study as many as 20 factors in a designed experiment and consequently not obtaining useful information. If you have good technical knowledge of your process, most injection molding experiments should not include more than four or five factors [2,3,5]. This greatly increases your chances of obtaining useful information. Given the response you have chosen to optimize, determine which factors you believe will have the greatest influence on that response.

Once you have chosen the factors, you must now select the factor levels you wish to explore. The levels for each factor represent the ranges over which you wish to explore the influence of the factor on the response.

DOE is not a panacea, it is a tool. It is not a substitute for knowledge of your technology. DOE incorporates current understanding of your technology. If you know “something” about your technology and use DOE wisely, it can help you tremendously.

A Process Diagram for an Injection Molding Experiment

Suppose our customer requests that we make a hinged box with a length of 16 +/- 0.20 inches. The thickness of the box will be 0.070 inches. The resin being used is GP polystyrene with a melt index of 8. We will be using a 100 ton press machine with a single cavity mold. We have already set the transfer point and performed a gate seal test. We have decided to fix all settings except for the Mold Temperature and the Hold Pressure. The response we wish to optimize is Length. Our Process Diagram appears as follows:



Below is a summary of the control factors, constant factors and the response for this experiment:

CONTROL FACTORS

Mold Temperature
Low Level = 70°F
High Level = 90°F

Hold Pressure
Low Level = 5000 psi
High Level = 7000 psi

CONSTANT FACTORS

Front Zone Temp. 400°F
Middle Zone Temp. 400°F
Rear Zone Temp. 400°F
Injection Limit Time 5 seconds
Holding Time 5 seconds
Mold Closed Time 25 seconds
Mold Open Time 3 seconds
Clamp Force 60 tons
Screw RPM 100
Screw Back 7 inches
Max. Inj. Pressure 20,000 psi
Back Pressure 2500 psi

RESPONSE

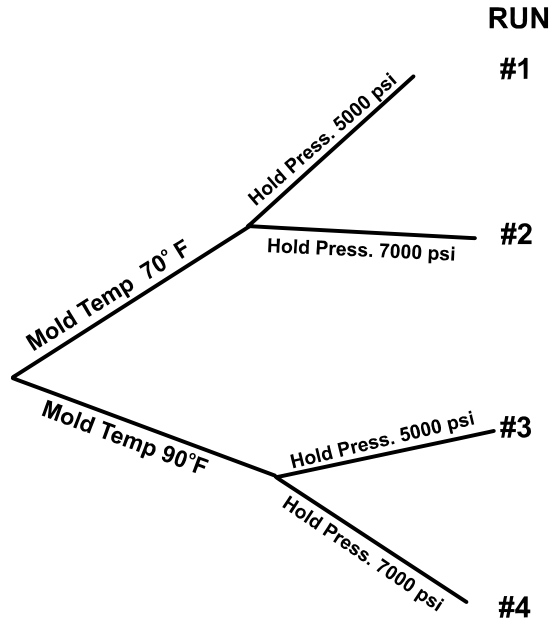
Length inches

An Orthogonal Array

A design type or design matrix (array) is a way to organize and track an experiment. In our example, we would like to conduct an experiment with the two factors at different settings and record the length of the part for each combination. Our technical knowledge suggests that the relationship between the factors and the response is linear. Therefore, we decide to look at only two levels of each factor -- a low level and a high level. The factors and corresponding levels would be:

FACTOR	LOW LEVEL	HIGH LEVEL
Mold Temp	70°F	90°F
Hold Press.	5000 psi	7000 psi

The tree diagram shown in Figure 1.1 illustrates the number of runs required if we were to experiment at all possible combinations of the factor settings.



The diagram shows that four runs are needed : $[(\text{number of levels})^{(\text{number of factors})}] = 2^2 = 4$. Placing these four combinations in the design matrix, Figure 1.2 shows we have:

Run	Mold Temp.	Hold Pressure	Length
1	70	5000	
2	70	7000	
3	90	5000	
4	90	7000	

Figure 1.2

Some of you might recognize this as a “4-corner” design. Each combination is known as a “run.” In this “orthogonal” or “balanced” matrix, we will arbitrarily assign the low value a -1 and the high value a +1. The previous design matrix can be rewritten with -1 and +1 shortened to “-” and “+”.

Run	Mold Temp.	Hold Pressure	Length
1	-	-	
2	-	+	
3	+	-	
4	+	+	

The matrix we have just built is orthogonal. That is, it is both vertically and horizontally balanced. For each factor, we will test at an equal number of high and low values (vertical balancing). For each level within each factor, we are testing an equal number of high and low values from each of the other factors (horizontal balancing).

Mathematically speaking, vertical balancing occurs if the sum of each factor column is zero. If the sum of each product column (Mold Temp x Hold Pressure in this example) is zero, then the matrix is horizontally balanced. A design is orthogonal if it is both horizontally and vertically balanced.

Run	Mold Temp.	Hold Pressure	Mold Temp. X Hold Pressure	Length
1	-	-	+	
2	-	+	-	
3	+	-	-	
4	+	+	+	
Sum	0	0	0	

If we test all possible combinations of our factors, our design matrix will be referred to as a **full factorial**. This will always be one of our design options; however, it is typically not our most efficient option.

Notice that in the table above, which illustrates horizontal balancing, we have created a new column in the design matrix. This will be used to examine the interaction between

Mold Temperature and Hold Pressure. The Mold Temperature \times Hold Pressure column is simply the product of the Mold Temperature column and the Hold Pressure column, row by row. The primary benefit of an orthogonal array is that it allows us to perform simple (but powerful) analysis and predictions.

Let's Collect Some Data

As you will recall from Figure 1.2, our design matrix is as follows:

Run	Mold Temp.	Hold Pressure	Length
1	70	5000	
2	70	7000	
3	90	5000	
4	90	7000	

Computer programs will often print out a “Worksheet” that looks similar to the design matrix above. This “worksheet” is given to the appropriate operators/engineers so they know how to set up the equipment for the experiment. Remember to set the constant factors to their appropriate values.

We will now conduct run 1 of the experiment by setting the Mold Temperature to 70° F and the Hold Pressure to 5000 psi. After completing the injection molding process under these conditions, we found the length to be 15 inches. For this example, we used SimTech-1 the Injection Molding Machine Simulator from Paulson Training Programs, Inc.[2].

We will now conduct run 2 of the experiment by setting the Mold Temperature to 70° F and the Hold Pressure to 7000 psi. After completing the injection molding process under these conditions, we found the length to be 19 inches.

We will now conduct run 3 of the experiment by setting the Mold Temperature to 90° F and the Hold Pressure to 5000 psi. After completing the injection molding process under these conditions, we found the length to be 12 inches.

We will now conduct run 4 of the experiment by setting the Mold Temperature to 90° F and the Hold Pressure to 7000 psi. After completing the injection molding process under these conditions, we found the length to be 17 inches.

Our completed worksheet will now appear as shown in Figure 1.3.

Run	Mold Temp.	Hold Pressure	Length
1	70	5000	15
2	70	7000	19
3	90	5000	12
4	90	7000	17

Figure 1.3

The Pareto Chart

Now it's time to let the software do the work. The purpose of this book is to simplify the design of experiments process. We could consume chapters discussing complicated statistical calculations but have discovered that often people get so overwhelmed by the calculations that they decide that design of experiments is not for them. It is unfortunate because DOE is a great tool to use! The good news is that there are several design of experiment software packages available to do the calculations for you. We have chosen to use *DOE Wisdom* for the examples in this book. The authors have worked as process/quality engineers in "the real world" for many years and realize that most of the "real workers" do not have three weeks to learn a software package. We have designed *DOE Wisdom* to be very user friendly yet very powerful. There is a special version of *DOE Wisdom* in the back of this book and Chapter 6 walks you through an example using the software.

DOE Wisdom will generate a Pareto chart for you. Figure 1.4 shows the Pareto Chart for our example. (NOTE: Appendix A discusses the calculations used for the Pareto Chart.) The Pareto Chart plots the impact (or effect) of the variable on the y-axis and the source of the effect on the x-axis.

A Pareto Chart is a chart of bars that are arranged in order of decreasing size. The bars represent the effect the factors have on the response.

If
e

Pressure has the most

The Main Effects Plot

Figure 1.5 shows the Main Effects Plot for our example.

The Main Effects Plot is a plot of the average of the data points at the low factor setting and the average of the data points at the high factor setting. The greater the slope, the more important the effect.

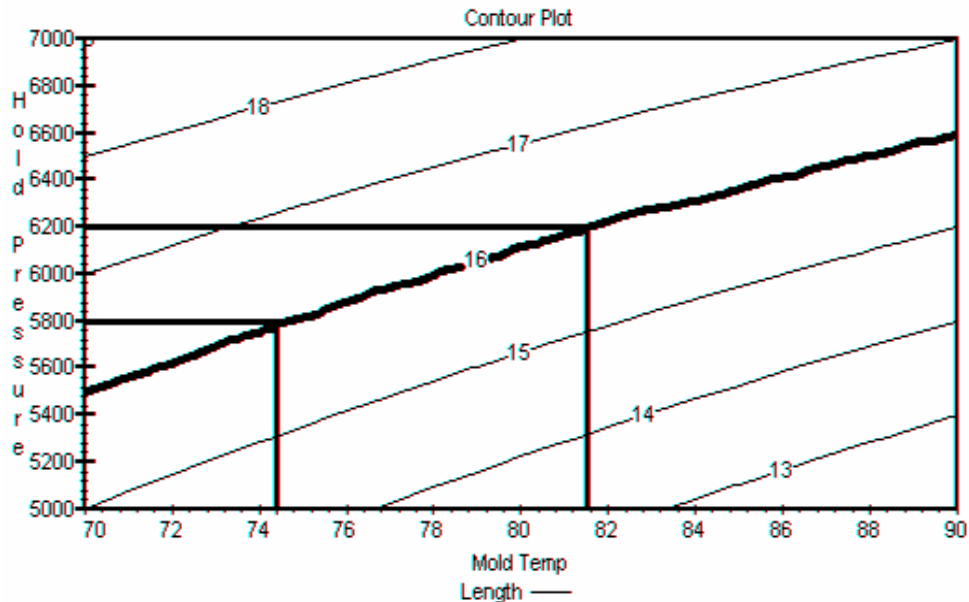
The response. at the low level (70°F) and Hold Pressure at the high level (7000 psi). If we wanted to minimize the length of our box, we would set Mold Temperature at the high level (90°F) and Hold Pressure at the low level (5000 psi). (NOTE: We will examine an interaction plot later in this book.) In our example, we want to hit a target other than the minimum or the maximum length. We want a length of 16 +/- 0.2 inches. We therefore need to look at the Contour Plot.

The Contour Plot

With the Contour Plot, we can target our response (length). Figure 1.6 shows the Contour Plot for this example.

Contour Plots are projections of lines of constant response from the response surface onto the two dimensional "factor" plane. Contour Plots provide the ability to graphically "see" those factor settings that the we Mold Pressure settings that fall on the 16 inch line will be the correct predicted settings. (Caution: These are only predicted settings ... we need to conduct additional tests to confirm the settings really do work!)

Figure 1.7 shows that Mold Temperature set at 81.7 and Hold Pressure set at 6200 gives a length of 16.0 inches. Additionally, Mold Temperature set at 74.3 and Hold Pressure set at 5800 also gives a length of 16.0 inches. Your particular choice of settings will depend on other considerations, such as lower cost or lower variability settings.



Summary

The purpose of this chapter was to give an overview of the basics of experimental design. In your *real* experiments, it is likely you will study more than two factors (3,4, or 5 are very typical for molders). Additionally, you most likely will have more than one response (length, width, appearance, etc.). The good news is that what we have covered so far is the foundation. If you understand the basics covered in this chapter, you are well on your way to understanding DOE. “Real world” experiments will merely build upon these fundamentals.

Design of Experiments is an excellent tool to use for evaluating injection molding processes. It can save time and money and can help injection molding companies increase their profit margins. DOE is **not** a difficult tool to learn. With the help of software, an experiment can be analyzed quickly and efficiently.

The Pareto Chart, the Main Effects Plot and the Contour Plot provide the basis for the analysis of any experiment. Probably 90% of what we need to know from an experiment can be obtained by interpreting these graphs. Of course there are other graphs and analysis techniques that help us know that additional 10% and they are discussed later in this book. These include:

Scatter Plots
Interaction Graphs
Response Surface Graphs
Analysis of Variance
Analysis of Means
Desirability Functions

Orthogonal arrays are typically used for designed experiments and in Chapter 1 we have looked at a full-factorial design. In Chapter 2 we will look at using fractional-factorial designs.

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