OPTIMIZING THE AUTOMATED PLASMA CUTTING PROCESS BY DESIGN OF EXPERIMENT

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Durga Tejaswani Vejandla

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OPTIMIZING THE AUTOMATED PLASMA CUTTING PROCESS BY DESIGN OF EXPERIMENT

Committee Members Approved:

Bahram Asiabanpour, Chair

Clara M. Novoa

Cassandrea Hager

Jesus A. Jimenez

Approved:

J. Michael Willoughby
Dean of Graduate College

To my parents

and brother,

inspired,

and inspiring.

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Durga Tejaswani Vejandla

Texas State University-San Marcos

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SUPERVISING PROFESSOR: BAHRAM ASIABANPOUR

Building complex two–dimensional metallic parts is difficult due to the physical properties of the metal, such as its solid nature, thickness, etc. Automated Plasma Cutting is an effective process for building complex parts in a short period of time. It cuts the metallic parts up to one inch thick with any given complexity, and with no usage of physical man power. Since, there are several possible machine settings (i.e., current, pressure, cutting speed, torch height, etc.), parts cut by using the plasma cutting process often lack good quality. Sometimes, these parts are not completely cut because the plasma gas does not penetrate all the way through the sheet metal due to insufficient pressure or excessive torch height, pressure, cutting speed or current. This research was conducted to discover the optimum machine settings by implementing a Design of Experiments approach (DOE) to find those relevant factors that affect the part's surface quality characteristics (i.e., surface roughness, flatness, accumulation underneath the work piece, bevel angles, and dimensional accuracy of the metal work piece). These important characteristics of part quality were considered as response variables. In this research, a response surface methodology approach and Desirability functions were used to optimize the automated plasma cutting settings. Final results identified an optimal machine configuration that facilitates the fabrication of parts with close-to-perfect quality for all 18 quality measurement responses.

CHAPTER I

INTRODUCTION

Background

Because of the growing need for manufacturing functional metallic parts, rapid manufacturing processes have become the focus of increasing research and development. Manufacturing processes based on material removal (i.e., drilling, milling, turning, and cutting) have been used for many years. According to Xiong (2008), the surface quality and accuracy of the parts are lower in direct metal prototyping when compared to machining. The recent advancements in manufacturing technology have enabled manufacturers to make parts and products faster, with better quality, and more complexity. Laser, water jet, and plasma techniques represent some of these newly established technologies in part manufacturing.

The process of plasma cutting was introduced in 1950. Since then, the manufacturing industries are using this process extensively because of its wide applications. In spite of its development, the field was given little attention by the researchers. The different processes included in the plasma cutting process are plasma-material interaction, process control, thermal plasma generation, liquid metal removal, etc. In the process of plasma cutting, a transferred electric arc is established between the negative electrode and the work piece within the cutting torch. The arc that is generated has to be narrow so that the power density is enough and the heat diffusion takes place very rapidly across the metal plate thickness. For cutting with plasma an adequate amount of power and force should be transferred to the work piece. Then, the work piece melts and the metal that is melted is removed from the cut.

By definition, plasma means a low-ionized gas, in which the individual atoms get ionized. In other words, plasma is a gas that is heated to a higher temperature and is ionized so as to become electrically conductive (Farnum, 2006). According to the Thermal Dynamics Torch Manual (2007), in the processes of plasma, the plasma gas transfers an electrical arc to the work piece. The heat of the arc melts the metal that has to be cut and removed. Another process of plasma is plasma gouging. This process removes metal to a controlled depth and width. Among several plasma applications, the cutting application is superior.

Problem Statement

In the plasma cutting system, a microprocessor is employed which controls electric current and gas flow simultaneously during the cutting process. However, due to various machine settings, the cut quality is not good at all times. Due to various setting combinations, it is difficult to have a cut without deformation, accumulation underneath the work piece and with good surface quality. Depending upon the cut type, i.e., straight, circular, or curve, different cut speeds are required. There is no exact cut speed which works well for all types of cut. The same problem exists with the torch height. Depending upon the type of application, the requirements of the cut quality differs. For the surfaces that are to be welded after cutting, bevel angle is a major factor. The cut direction also plays an important role in the cut quality. According to the Thermal Dynamics Manual (2007), if the cut is seen along the travel direction, then the right side of the cut is squarer than the left. This is because of the swirl effect of the plasma gas.

The factors that are responsible for quality can be identified to some extent on studying the behavior of the plasma gas such as insufficient penetration, main arc extinguishing, excessive accumulation underneath the work piece, and shorter tool life. Surface quality seems to be affected by the following seven machine parameters: pressure, cut speed, torch height, tip type, slower on curves, cut direction, and current.

Research Purpose and Scope

The primary objective of this research was to find the optimal parameter settings for the automated plasma cutting process. This was done by using the Design of Experiments (DOE) approach considering all the seven independent variables and three levels of these independent variables (i.e., high, medium and low). The independent variables and their effects on cut quality responses are shown in the Fig 15.

Regression analysis was developed and used to identify the effect of independent variables on the responses. Then, after identifying the most important factors, a Desirability function was developed to find the optimal parameter settings. Regression analysis explores the relationships between several independent variables and one or more response variables. Regression analysis and Desirability function helps in evaluating factors that have a statistical significant effect in surface quality characteristics. These characteristics are measured depending upon their type and effect.

Organization of the Thesis

The rest of the thesis is organized as follows. Chapter II entitled "Types of Sheet Metal Cutting" gives a general idea on different types of sheet metal cutting. It reviews Laser Cutting, Plasma Cutting, and Water Jet Cutting in brief, as well as their functionality and applications in the manufacturing industry.

Chapter III entitled "Research Methodology" explains the Analytical Research and Experimental Research and the procedure that is employed in each one. The Analytical Research is shown with a goal hierarchy plot with different sublevels, starting from the main goal of the research.

Chapter IV entitled "Independent and Dependent Variables" describes the independent and the dependent variables. The chapter also presents all the independent variables, their levels, the selection of experimental region, Design of Experiment, response variables, and different instruments and their measuring methods. Chapter IV also includes the description of the geometry of the part and describes each response variable in detail with their measuring method and tool. This section also reviews the previous conducted research efforts in this area and their results.

Chapter V entitled "Results" presents the results. The results are shown by taking into consideration each response and the important factors that are affecting them. The chapter also includes the definition of the Desirability Function and the need for it in the research. Then, the optimal parameter settings are identified and shown. Validation of the model was also developed by taking into consideration all the independent variables.

Chapter VI entitled “Conclusions and Future Research” presents the conclusions of the research and suggests the new direction for future research.

CHAPTER II

LITERATURE REVIEW

Ramakrishnan et al. (1997), in their research reported that the force of the plasma jet has a linear relationship with the pressure at the nozzle exit. They also reported that the power in the plasma was increased with the current density, current, and the mass flow rate. They concluded that, to reduce the accumulation underneath the work piece for a straight cut, high power density and high pressure are needed. When the pressure was not adequate, the metal that was melted was not removed completely from the work piece and moreover some part of it accumulated underneath the work piece.

Design of Experiment Approach

According to Myers and Montgomery (2002), DOE is a structured, organized method for determining the relationship between factors (Xs) affecting a process and the output of that process (Y). According to Hefin and Jiju (2003), DOE is a special technique to study the effect of several independent variables that are affecting the response. To minimize the number of the experimental runs and complexity of the DOE, a good fit between the model and the process is necessary (Pfaff et al., 2006).

Introduction

In 1920's England, Sir R.A. Fisher introduced this new statistical technique named Design of Experiments. With this technique, all combinations of factors were laid and multiple variable effects were studied simultaneously. He modified DOE and utilized a standard form of it in his experimental study. During the Second World War, Taguchi, a Japanese scientist, introduced a new statistical technique named Taguchi's approach. The difference between DOE and Taguchi's approach is that Taguchi used special application principles.

Full Factor Designs

According to Myers and Montgomery (2002), Full Factorial Design is a design in which all possible combinations of the factor levels are fulfilled. The result from the full factorial experiments would be more reliable but conducting the full factorial experiments is costly and sometimes prohibitive (Roy, 1947). Even though we have a limited number of factors, the number of experiments is large in number because we are considering all possible combinations.

Design of Experiments using Orthogonal Array approach

The purpose of this section is to give the reader a brief description on the Orthogonal Array approach. This technique is economical. If the effects of individual factors on results are studied, then it will be easy to choose the best factor combination. In the Orthogonal Array approach, all the possible conditions are not tested. Only a small fraction of them are tested. Depending upon the number of factors and their levels, the necessary number of conditions is decided. With the use of Orthogonal Arrays, which are special tables of numbers, the layout of the experiments is accomplished.

Introduction

According to Roy (1947), a set of tables of numbers in which each of the numbers is used to layout the experiments for a number of experimental situations is called Orthogonal Array. Designing the experiment with the use of these arrays is simple. Notation L with a dash or subscript designates the array. The numbers of combinations prescribed by the design are indicated by the number of rows in the table and also indicated by the subscript. Since in an Orthogonal Array, each column should be balanced, then all array columns become balanced too.

Special Properties of Common Orthogonal Arrays

- L-4,L-8,L-12,L-16,L-32 are the five two level arrays and each of these arrays has one column fewer than row (i.e., L-4 have 3 and L-8 have 7 and so on). The sample L-8 Chart is shown in the following Fig 1.
- L-9 have 4 three level columns, L-18 have eight columns, and L-27 have 13 columns.
- The two level array modified forms are 2 four-level arrays (Roy, 1947).

Orthogonal Array L_8 (2^7)

	FACTORS						
TRIAL NUMBER	A	B	C	D	E	F	G
1	0	0	0	0	0	0	0
2	0	0	0	1	1	1	1
3	0	1	1	0	0	1	1
4	0	1	1	1	1	0	0
5	1	0	1	0	1	0	1
6	1	0	1	1	0	1	0
7	1	1	0	0	1	1	0
8	1	1	0	1	0	0	1

Fig 1. The sample L-8 Chart

Steps in Designing an Experiment with Orthogonal Array

a. Selecting the Orthogonal Array**:**

According to Roy (1947), in the selection of an array no mathematical formula is required and it is simple and easy. While selecting the array, the maximum number of experimental conditions which equals the number of rows should be known.

b. Assigning Factors to Column**:**

Assigning factors to columns do not have any particular order. Any of the columns can be assigned to any one of the factors.

c. Describing the Experiment:

Rows represent individual experiments. These experiments are read by the cryptic notation which is then followed by the description of the experiment.

Mathematical Models

In DOE, synergy between mathematical and statistical techniques such as Regression, Analysis of Variance (ANOVA), Non-Linear Optimization, and Desirability Functions helps to optimize the quality characteristics considered in a DOE under a cost-effective process. ANOVA helps to identify each factor effect versus the objective function (Wang et al., 2007). Response Surface Regression methodology is an assortment of mathematical and statistical techniques useful for modeling and analyzing experiments in which a response variable is influenced by several independent variables. It explores the relationships between several independent variables and one or more response variables; the response variable can be graphically viewed as a function of the process variables (or independent variables) and this graphical perspective of the problem has led to the term Response Surface Methodology (Myers and Montgomery, 2002). Response Surface Methodology is applied to fit the acquired model to the desired model when random factors are present. Response Surface Regression may fit linear or quadratic models to describe the response in terms of the independent variables and then search for the optimal settings for the independent variables by performing an optimization step. According to Clurkin and Rosen (2000), the Response Surface Method was constructed to check the model part accuracy which uses the build time as functions of the process variables and other parameters.

According to Asiabanpour et al. (2005), development of the regression model describes the relationship between the factors and the composite Desirability. Response Surface Methodology also improves the analysts' understanding of the sensitivity between independent and dependent variables (Bauer et al., 1999). With Response Surface Methodology, the relationship between the independent variables and the responses are quantified (Kechagias, 2007). A new experimental design is run around the values of the optimum found and the process of fitting a model and searching for an optimal combination of independent variables that optimize the response may be repeated several times. As the main purpose of this research was to find the levels of the factors that optimize the part quality cut, we used the Response Surface Regression technique. Some of the mathematical and statistical techniques embedded in Response Surface Methodology are ANOVA and Desirability Function. Furthermore, when there are many responses to optimize, a Desirability function is used. It combines individual Desirability functions for the responses. It considers that each function represents the limits in which a quality characteristic must be, and thus each one ranges between zero and one. When there is presence of non-uniform control factors, Desirability function is used to determine the optimal parameter settings of the process (Robinson et al., 2006).

Proposed Procedure

This study proposes a new approach to identify the optimal parameter settings of the plasma cutting process. First, factors that have a statistical significant effect on surface quality were determined. Second, the experiment is designed using Design of Experiments approach (DOE) and the runs required are performed. Third, the identification of the important characteristics of surface quality as responses and measuring the responses independently is performed. Fourth, the Regression Analysis is performed to identify statistically significant factors, and develop the corresponding

Regression model. Finally, the optimal parameter setting is identified using the Desirability Functions.

2.2 Types of Sheet Metal Cutting

In this chapter, different types of sheet metal cutting and their benefits are proposed. The applications of these types of sheet metal cutting are also discussed in this chapter. Finally, their advantages and disadvantages are explained.

2.2.1 Laser Machining

These days, among several manufacturing processes for the fabrication of metal, Laser Beam Machining has dominated the conventional methods and also the manufacturing industry. This is due to the laser’s inherent ability to perform multiple operations in a single setup which contributes to shorter total-processing times. Power, software, and process improvements spell work for lasers (Benes, 2004).

According to Dekker (2003), Laser Beam Machining is a thermal material removal process which utilizes a high-energy coherent light beam. The beam melts and vaporizes particles that are on metallic and nonmetallic surfaces. The term LASER is an acronym which means the Light Amplification by Stimulated Emission of Radiation. The laser, with stimulation and amplification, converts electrical energy into a high-energy density beam (Decker, 2003).

The Laser Beam Machining is used for several operations such as Drilling, Cutting, and Milling, etc. According to Schlueter (2007), the use of the laser in the manufacturing industry has become a highly established process. The use of laser technology improves efficiency and quality and also makes handling easy. Additionally, the quality of the product is very high.

Cutting with the use of laser technology is a thermal and consolidated industrial process. The process implies the least material wastage; the distortion of the parts becomes less even for medium and low thickness sheets and prevents the tools from tear and wear (Lamikiz et al., 2006).

High speeds cannot be achieved by moving laser systems and these are restricted to flat sheet cutting. Moving optics can have cutting speeds that exceed 100 m/min. and these machines can move work pieces or three-dimensional static work pieces. The moving work piece lasers are the same as the traditional turning and milling lasers (Dekker, 2003).

There were also some disadvantages with the laser cutting, which led to the invention of plasma cutting. According to Brown (1999), the limitations of laser cutting are relatively slow speed in the operation and that slow speed limits the volumes that it can produce. The installation and the operational costs are also high for laser cutters, and the dangers that are associated with their working became their main disadvantage. So, the manufacturers turned towards the Plasma Cutting and Water Jet Cutting.

2.2.2 Water Jet Cutting

According to Farnum (2006), many manufacturing industries are using water jet as it is faster when compared to laser and plasma and is able to tackle thinner materials and can yield good turnover and productivity. The setup time for water jet is less when compared to other similar technologies. According to Aronson R.B. (2007), water jet not only speeds up the production but also eliminates several manufacturing steps. The side forces in water jet cutting are minimal. In the machine tool market, it is the fastest growing segment (Farnum, 2006).

In the initial stages, materials such as fabric, thin metal, and thick parts were only fabricated with water jet. This was because of the complexity incurred during some operations, high noise, and serious maintenance problems. But today, it has become a well established industrial process because of its production speed which eliminates many manufacturing steps. It is a powerful, accurate and versatile machine that is competing with other technologies. Wear is much less in water jet machines when compared to high pressure machines and that reduces initial and maintenance costs.

Fig 2. Water jet Cutting taken from howstuffworks.com

The advantage of water jet is that it can be used for a broader range of materials. According to Koelsch (2005), regardless of composition, water jet can cut many materials. It is capable of cutting parts with scale on surfaces of insulators such as glass, ceramic, etc. Another advantage of water jet is that delamination is not produced. As the speed of the cut increases, the cost decreases, and the abrasive flow rate increases.

2.2.3 Plasma cutting process

2.2.3(a) Plasma cutting

The need for plasma cutting increased when low volume pressed metal panels and tubes were required to cut, trim, and be pierced. A high velocity gas jet is used for Plasma cutting. The process is based on resistive heating. The high velocity gas is heated by an arc struck between an electrode and the work piece, which makes it electrically conductive. The arc is concentrated using an annular air or water jet. The jet provides the control for the arc and the energy density that is needed for rapid penetration and it can cut many types of metals up to 20 mm thick (Kirkpatrick, 1998).

According to Kirkpatrick (1998), specialized nozzle systems are used by high definition plasma systems which utilize magnetic fields or enhanced gas flow arrangements to constrict the arc very tightly. The energy density is thus raised by a factor of three to five providing a narrow arc. This narrow arc will have a much shallower temperature gradient when compared to conventional plasma. As thin materials are less likely distorted, a lower overall input energy can be used for this type of process (Kirkpatrick, 1998).

According to Farnum (2007), the cutting speed of plasma is four times faster than any other oxy fuel. The cuts are also very clean as plasma uses dry air in most of its applications. Less clean up is required for plasma as it produces a narrow cut with a small affected heat zone. Plasma cutting can be used for a variety of materials including aluminum, stainless steel, and mild steel. Raising the energy density makes the cut faster and creates better edge quality. But too high energy densities increase wear and operating costs (Farnum, 2006).

A cleaner and accurate cut can be produced when oxygen is used as ionized gas but the operation costs for this would be higher when compared to nitrogen. For a longer life system, a microprocessor which controls electric current and gas flow simultaneously during the cutting process has to be employed (Farnum, 2006).

2.2.3(b) Plasma CAM

In recent years, Plasma CAM has combined plasma-based cutting technology (Kirkpatrick, 1998) with computer numerical control (CNC) systems to perform complex cuts in a short period of time. The Plasma CAM system uses 2-D CAD drawings of the part geometry to generate a cut path. This computer-generated cut path is then used to control the movement of the plasma torch (i.e., a component of the automated Plasma cutting tool that is installed on a robotic XY table). Parts up to one inch thick and with high shape complexity can be made with the Plasma CAM systems. The Plasma CAM cuts the metal in a synchronized manner. It utilizes the current and the pressure for its operation. The speed and the cutting height can be adjusted. It can cut the metal in a very short time when compared to other laser cutters. According to Defalco (2007), the technology that is used in this machine offers the benefits of fast, high quality cutting which results in high demand for this equipment. The finishes are good with this machine, which reduces the cost for refinishes. Improved tolerances for the cut parts have also expanded the use of this machine.

Fig 3. Plasma CAM machine taken from the PlasmaCAM.com.

2.2.3 (c) Process of Plasma CAM

Plasma CAM uses computer software for its operation. The design can be drawn on the system's software or can be drawn and saved in DXF format by other CAD software. The Plasma CAM software produces the cutting path and sends the required code to the cutting mechanism. The cutting mechanism works with an electric arc through a gas that is passing through a constricted opening. The gas that is utilized may be oxygen, nitrogen, argon, etc. High temperatures produced by the system melt the sheet metal. As the metal that is being cut is a part of the circuit, the electrical conductivity of the plasma causes the arc to transfer to the work piece. The high speed gas and high temperature causes the metal to melt and cut through it. The cut is protected as the gas is directed around the perimeter of the cut area. Sometimes, a pilot arc can also be placed between the electrode and the nozzle to ionize the gas, and this makes the metal melt. This generates the plasma gas prior to the cut. The working process of the plasma cutter is shown in Fig 4 (Thermal Dynamics 1Torch™ Instruction Manual, 2007).

As shown in Fig 4, (Thermal Dynamics 1Torch™ Instruction Manual, 2007) in a Plasma Cutting Torch a cool gas enters Zone B, where a pilot arc between the electrode and the torch tip heats and ionizes the gas. The main cutting arc then transfers to the work piece through the column of plasma gas in Zone C.

By forcing the plasma gas and electric arc through a small orifice, the torch delivers a high concentration of heat to a small area. The stiff, constricted plasma arc is shown in Zone C. Direct Current (DC) straight polarity is used for plasma cutting, as shown in the illustration.

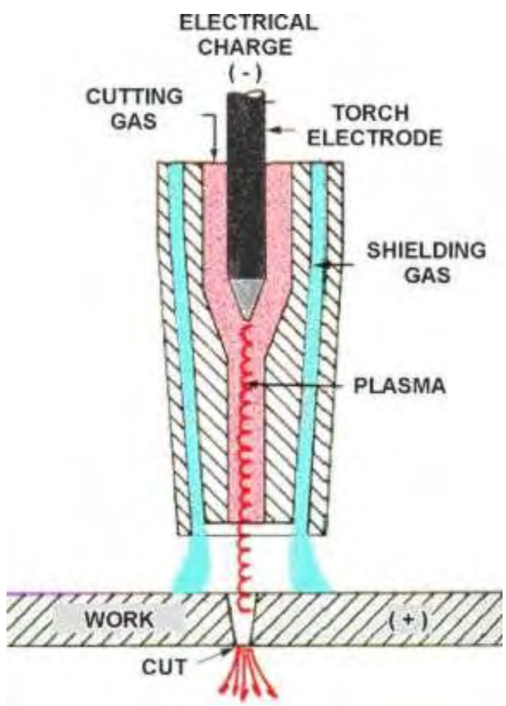

Fig 4. Working process of Plasma CAM taken from wikipedia.org

Zone A channels a secondary gas that cools the torch. This gas also assists the high velocity plasma gas in blowing the molten metal out of the cut, allowing for a fast, slag-free cut (Thermal Dynamics 1Torch™ Instruction Manual, 2007).

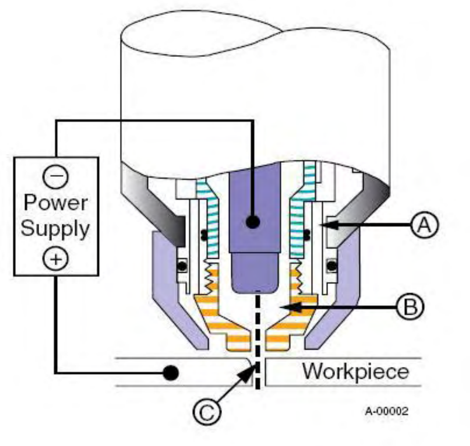

Fig 5. Structure of the plasma cutting system (Thermal Dynamics 1Torch™ Instruction Manual, 2007).

Plasma Cutting has many benefits when compared to other technologies. It cuts faster and does not require a pre-heat cycle. The width of the cut is precise and has an ability to tackle thicker materials.

The drawbacks of Plasma Cutting are a large heat affected zone is created surrounding the part and it forms dross, the re-solidified material which forms at the bottom of the cut. It is difficult to have a perfect setting of the parameters for a better result. So, there is a need for the optimization of the process which uses the empirical model to identify the levels of the input variables that result in the best values of the response.

CHAPTER III

3.1 RESEARCH METHODOLOGY

Since the introduction of the plasma arc cutting process in the 1950s, there has been a steady growth in its use in the metal fabrication industries for profile cutting of metallic sheets and plates. Despite superior industrial developments that have taken place, the process has received very little attention from the scientific community on any of the scientific aspects of the process, including thermal plasma generation, plasma-material interaction, liquid metal removal, and process control. The different activities that are employed in this research are categorized into two groups: analytical research and experimental research. These activities are dependent on one another. The theoretical study and experimental research are done simultaneously as shown in Fig 6.

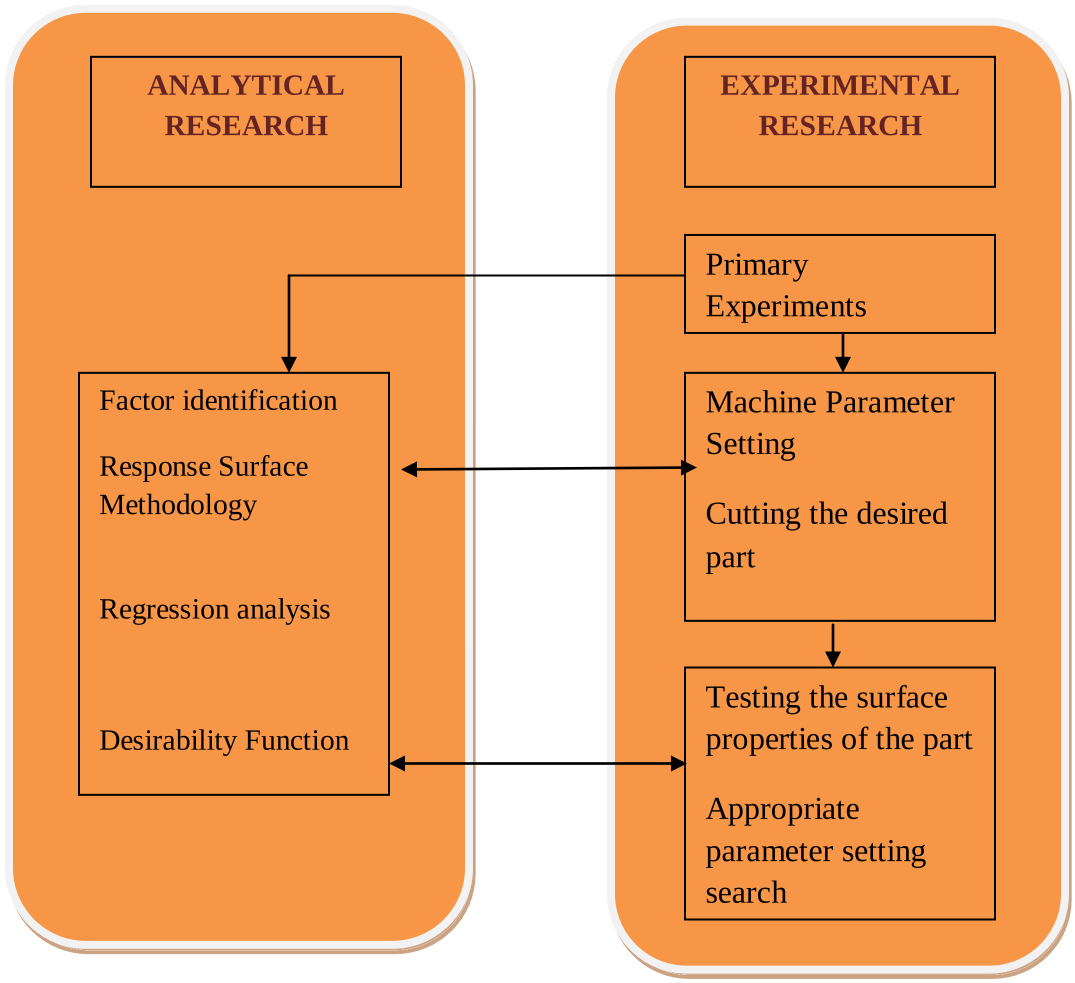

Fig 6. Research Methodology

3.1Experimental Research

In the experimental research, many parts were fabricated. In addition, as part of the research, numerous experiments were conducted to find better surface quality of the cut. These include experiments with machine parameter variation (e.g., cutting pressure, voltage, cut height etc). The primary reason for experimental research was to discover or identify the factors that most affected the part quality. Primary settings for factors in conducted experiments in this stage were assigned through the one-factor-at-a-time method.

3.2 Analytical Research

The analytical research was designed by applying a goal hierarchy plot (Barton R.R., 1999). Goal hierarchy plot contains several goals. The general goals occur at higher levels of the plot. Fig 7 shows the hierarchy plot for the Plasma CAM operation. In this research, the top-level goal (finding the appropriate set of parameters for a better cut quality) was satisfied by accomplishing a 2nd level sub-goal by identifying the responses (i.e., cut quality, accumulation underneath the work piece, flatness and dimensions of the part). To achieve the 2nd level sub-goal, identification and control of effective factors on any item of desirable specification were necessary. Factor identification and control are shown in the 3th level sub-goal. The lowest-level sub-goal (level 4), Design of Experiments, theoretical studies, and response surface methodology, helps to achieve the 3rd level sub-goal. In practice, first by studying the related literature and theories and by designing and conducting experiments, the factors related to the 3rd level sub-goal are identified. The results were obtained using Response Surface Methodology. So, they occupied the 4th level in our hierarchy plot.

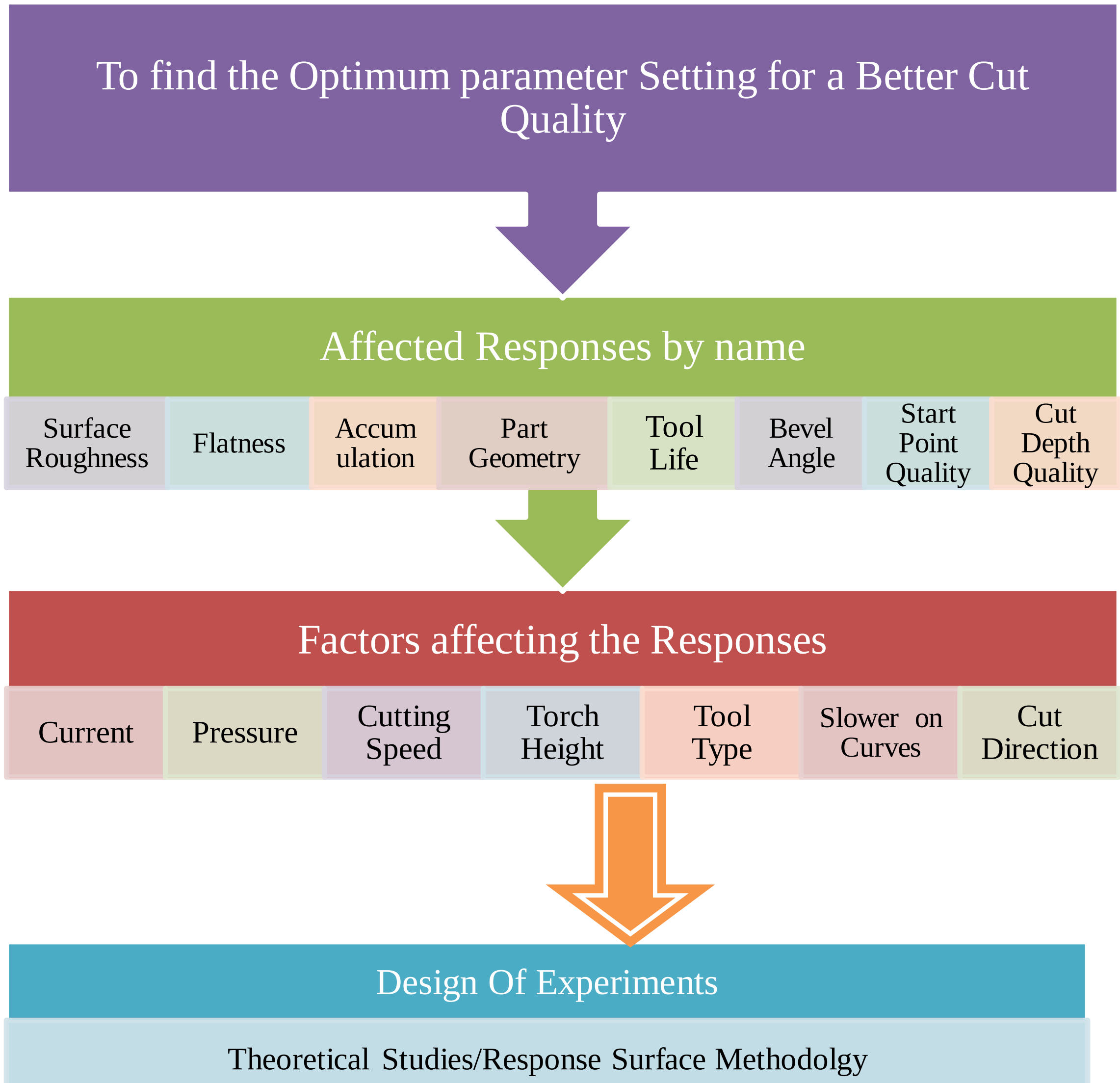

Fig 7. Goal Hierarchy Plot

CHAPTER IV

INDEPENDENT AND DEPENDANT VARIABLES

4.1 Factor Identification and Classification

Previous research and preliminary experiments helped to identify the factors for the experiments and also to find the appropriate parameters for a better cut quality. For this purpose seven factors are selected for our new experiment. Based on the preliminary experiments and the Plasma CAM machine manuals, the following variables seem to be the most influential factors on the part quality: current, pressure, torch height, slower on curves, tool type, and cut direction.

A: Current

This factor was among the suggested variables by the Plasma developers (Thermal Dynamics 1Torch™ Instruction Manual, 2007). Cutting power is dependent only on the type and thickness of the material being cut. The amount of variation allowed by the Cut Master™ 101 was 20A to 80A. The 20A to 40A range was used for drag tip cutting where the torch tip touches the work piece on thin plates of quarter inch thick mild steel.

The 40A to 80A range was employed for standoff cutting, where the torch tips do not touch the work piece. The discrete range used for investigation was 40A, 60A, and 80A. Typical results from insufficient cutting power proved to be cuts that did not penetrate all the way through the thickness of the work piece. Whereas, typical results from too much cutting power were kerf width too great, excessive dross build up due to extreme heat, and poor cut surface quality (Thermal Dynamics 1Torch™ Instruction Manual, 2007).

B: Pressure

Pressurized air serves two purposes in plasma cutting. The primary purpose is to supply gas to fuel the plasma reaction, and the secondary purpose is to blow melted material away while cooling the tip. Pressure was determined as a variable affecting quality by the Plasma CAM machine Manual. According to Wichern et al. (2005), the pressure during testing affects the roughness. Operating pressure range as given by the user manual was listed as 60 psi to 75 psi; less than 60 psi triggered a safety in the Cut Master™ 101 and prevented operation. A maximum pressure input of 125 psi was also listed. Operating pressure was found to be 70 psi for all cutting power levels (Thermal Dynamics 1Torch™ Instruction Manual, 2007). A combination of operating range and experimentation determined that the discrete range used for investigation was 60 psi, 75 psi, and 90 psi. Insufficient pressure results in the Cut Master™ 101 operation prevention for safety purposes. Typical results from excess pressure were poor cut surface quality, excessive top spatter, and poor bevel angle (Thermal Dynamics 1Torch™ Instruction Manual, 2007).

C: Cut Speed

The cut speed is the speed at which the torch moves in the X-Y plane while the torch is cutting. Cut speed varies depending on material type, material thickness, and input power. Material thickness and type were constant and then cut speed was dependent only on input power. Both the cut speed and input power are input variables for the Plasma CAM system. The Plasma CAM user manual states that the cut speed may vary by as much as 50% of the given value, i.e., 110 (Thermal Dynamics 1Torch™ Instruction Manual, 2007). Therefore, the feasible range of speeds was found to be in between 10 ipm and 100 ipm (inches per minute). Typical results from high cut speed were high speed dross, poor bevel angle, and cuts that did not go completely through the thickness. Typical results from low cut speed were slow speed dross, unstable arc, and loss of arc (Thermal Dynamics 1Torch™ Instruction Manual, 2007).

D: Torch Height

Torch Height is the distance between the tip of the torch and the work piece. Standoff distances of 1/8 inch to 3/8 inch were proposed in the 1Torch™ instruction manual. The feasible range of torch height was found to be in between 0.1 inch and 0.3 inch. A typical result from cutting too close was that the tip would touch the work piece thus triggering a safety built into the Cut Master™ 101, which would drop the current to 40A. Typical results from cutting too far away were excessive top spatter, poor bevel angle, and cuts that did not go completely through the thickness.

E: Tool Type

Tool type referred to the type of tip used for cutting. The 1Torch™ came with several tip options which differ based on cutting power. The cutting power range used was 40A to 80A and tips were obtained for that entire range. The available tools for this research were 40A tip, 60A tip, and 80A tip.

F: Slower on Curves

The machine has the ability to slow down when going around corners, for a better cut. If slower on curves is greater than 0, then the machine reduces its speed when cutting curves and circles. This means that straight cuts use different speeds than circular, semi-circular or curved cuts. The larger the number, the more it slows. The range for this factor was identified by experimentation. The range that is observed for this variable is 0 to 4 (Plasma CAM manual, 2001).

G: Cut Direction

Cut direction is simply the direction in which the cut is made. Two types of cuts were considered for comparison. These were Vertical-direction cuts and Horizontal-direction cuts. In other words, we cut a part first in one direction and then we rotate the part 90 degrees around the point and made the other cut.

4.1.1 Noise Factors

According to Arvidsson and Gremyr (2008) noise factors are those forces that cause deviation from target and are out of the control of the experimenter. These factors are simply sources of variation and have an affect on the response but their affect was uncontrollable. The noise factors in this experiment were temperature and humidity of the air. This was because the sheet metal gets heated up to different temperatures since the runs were done continuously. This was uncontrollable. So, we considered it as a noise factor. According to Suwanprateeb. J (2007), direct contact of the metal with the water or exposure to humidity degrades the material's mechanical and physical properties. The humidity in the air also affects the sheet metal and it is uncontrollable.

4.2 Selection of Experimental Region

The optimization started by conducting an investigation on the conditions that are essential for a better cut quality. For this purpose many experiments were conducted.

The seven variables or factors and the levels that are potentially affecting the parts quality are shown in the following Table 1.

Design Expert Software was used in this research for planning the experimental design

Table 1. Summary of the variables and their levels.

A.Current	**Amps**
Level 1:	40
Level 2:	60
Level 3:	80
B. Pressure	**psi**
Level 1:	60
Level 2:	75
Level 3:	90
C. Cut speed	**ipm**
Level 1:	10
Level 2:	55
Level 3:	110
D. Torch height	**in.**
Level 1:	0.1
Level 2:	0.2
Level 3:	0.3
E. Tool type	
Level1: (E_0)	a
Level2: (E_1)	b
Level3: (E_2)	c
F. Slower on curves	
Level 1:	0
Level 2:	2
Level 3:	4
G. Cut Direction	
Level1:(G_0)	Vertical
Level2:(G_1)	Horizontal

Three levels are considered for six of the factors (1= low, 2 = medium and 3 = high), and 2 levels are considered for the cut direction (horizontal and vertical directions). The Response Surface function curvature is also looked. So, this is the best way to fit a regression model which relates the response to the factor levels. Two replicates were used for DOE. The number of runs for a full factorial experiment is $3^6 \times 2^1 \times 2$ (replicates) = 2916. The Orthogonal Array approach was used to reduce the number of runs and still obtains the maximum information which allows easy interpretation of results. Among the Orthogonal Array approaches, an L- 18 Orthogonal Array is selected and augmented with 71 additional runs to estimate the two factor interactions. All 89 experiment settings were shown in Appendix A.

Mixed levels of factors are present in this research (i.e., six of them are at 3-levels and one is a 2-level). During interpretation of the results, we are considering only two factor interactions were considered, as higher factor interactions are difficult to interpret and are assumed as negligible.

There was a possibility of missing data as some of the responses cannot be measured if the part wasn't cut. There are two approaches in missing data analysis. They are:

1. Approximate Analysis: In this type of analysis, the missing observation is estimated and the analysis of variance is performed with that data as it were the real data. The error degrees of freedom are reduced by one for each missing observation.

2. Exact Analysis**:** In this analysis, the missing data makes the design unbalanced. The fitted values for the observation are found from the solution to the normal equation and the ANOVA is done through a general regression significance test. This Research uses the Minitab software that excludes the missing observations from the row they are in and accordingly the regression model is adjusted.

4.3 General Equipment for Measuring Responses

4.3.1 Measuring Tool for Surface Roughness

Due to the complexity and size of the part, available surface roughness (finish) standard mechanisms were not applicable. Instead, a rating system was designed to rate the surface quality. The rating system scale was between 1 (very rough surface) and 10 (perfect surface finish). For each rate, a representative object was found.

4.3.2 Measuring Method

To measure surface roughness, each area of the part was compared to representative objects, to find the most similar one. The surface quality of each part was evaluated by three researchers and a medium rating was used for the optimization calculations.

4.3.3. Surface Variation Tool

A surface variation measurement gauge was used for measuring the flatness. This tool gives the values and the variation in the surface when the surface is moved smoothly under the gauge. The tool was produced by Starrett.

4.3.4. Electronic Vernier Caliper

An electronic caliper was used for measuring the dimensions of the part. Dimensions are measured by placing the part in between the knobs and the caliper reads the dimensions in inch or mm.

4.3.5 Protractor with a sliding scale

A protractor with a sliding scale was used for measuring the bevel angles of the part. The protractor was a normal one with a scale which slides at its back.

The measurement was taken by keeping the scale parallel to that side where the angle had to be measured and the protractor reads the angle.

4.4 Mechanical and Physical Part properties

4.4.1 Part geometry

Stainless steel sheet metal with 0.25 inch thickness was selected as the part type for the experiments. The part was 4x4 inch in vertical and horizontal direction. It has a semicircle of radius 2 inches and an inner circle of radius 1.5 inches.

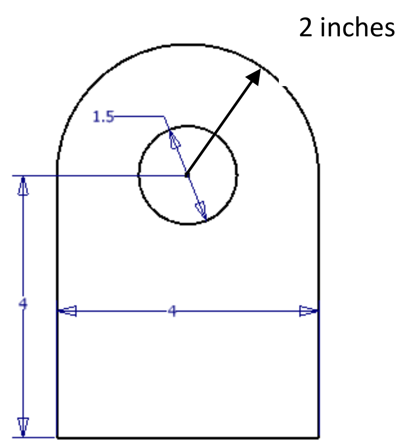

Fig 8. Geometry of the experimental parts in inches

4.4.2 Surface Roughness Responses

Many new technologies are being used for surface quality evaluation. Alabi (2007) and his team used Fractal Analysis to characterize the surface finish quality of the machined work -piece. They proposed a process monitoring approach for measuring surface quality. This process monitoring assists the work piece quality in machining. The machined surface quality is correlated after broaching with the output signals which are obtained from cutting forces, vibration, acoustic emission, and multiple sensors. The machined surface quality is estimated in terms of burr formation, surface anomalies, geometric accuracy and chatter marks. Factors such as tool settings, coolant conditions and cutting speed are set in the form of an orthogonal array based on the cutting condition variations. At every level of tool wear each orthogonal array is repeated. The geometric deviation, burr formation and even the chatter marks to a small extent of the machined profile are detected by the cutting force signals which are sensitive to detect. To develop appropriate techniques for qualitative and quantitative evaluation of the machined surface quality, the output signals time and frequency domain analysis is carried out (Axinte et al., 2004).

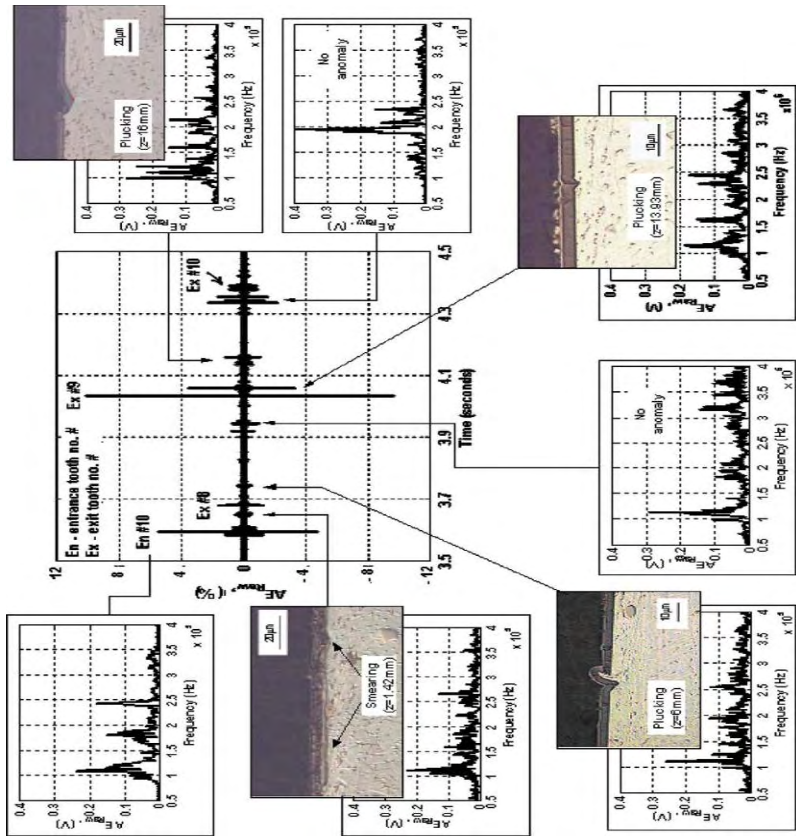

Fig 9. Example of spectrum analysis of the AE signal to support the identification of surface anomalies. Cutting conditions: work piece: Inconel718; v ¼ v1; tool setting: roughing and burnishing taken from the paper by Axinte et. al, 2004. p.no.1103. tool segments; coolant off; tool with all teeth uniformly worn at VB= 0.25 m.

In the research by Axinte et al.(2004) the response was measured for three different areas.

1. Straight Line

2. Internal Curve

3. External Curve

4.4.2.1 Straight Line Response

The straight line on the part was selected as one of the areas for measuring the response variable surface roughness. This was measured using rating system described in 4.4.1.

4.4.2.2 Internal Curve Response

There was an internal curve in the model which was one of the responses for surface roughness. This response was also measured with the rating system.

4.4.2.3 External Curve Response

There was an external curve in the model and it was selected as one of the responses. It was measured with the rating system.

Because of lack of access to the tool the measuring method for surface roughness used by Axinte et al.(2004) was not used in this research.

4.4.3 Flatness Response

Among many methods that are available for measuring flatness, Marsh et al. (2006) used interferometric measurement to determine the Flatness of a work piece in ultra-precision fly cutting. This cutting process was characterized by depths of cut that ranges from 25 micrometer to 1 micrometer or less for finishing cuts (Marsh et. al. 2006). The model used in this research was an important and useful tool for improving the resultant flatness of the fly cutting operation and was based on the work piece geometry and spindle speed. The results imply that the spindle speed that was preferred for the ultra precision fly cutting should be chosen in a way that the structural resonance dominance should not occur at an integer multiple of the spindle speed. The process condition's exact phasing of the trial work pieces can be verified by the inspection of interferometer (Marsh et al., 2006).

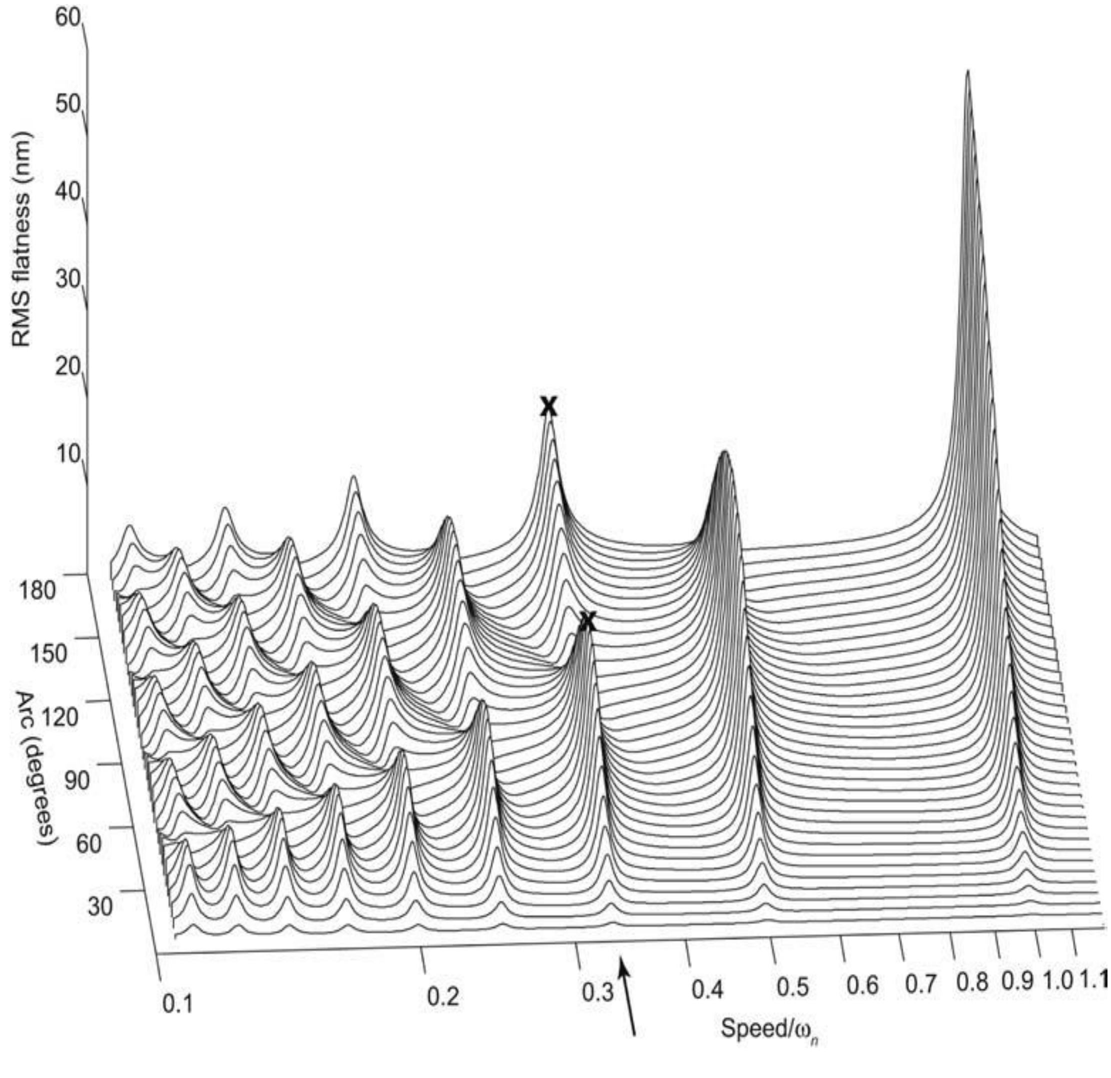

Fig 10. Effect of work piece size on flatness taken from Research paper by Marsh et al., 2004. pp no.216.

As the accuracy in micro inches was not needed in this research, the method designed above was not used. In this experiment, flatness of the work piece was measured with the tool mentioned in Fig 10 to identify the part deformation.

4.4.3.1 Measuring Tool

A surface variation measurement gauge was used for measuring the flatness. This tool gives the values and the variation in the surface when the surface is moved smoothly under the gauge. A surface variation tool is shown in Fig 11.

Fig 11.Surface Variation Measurement Tool

4.4.3.2 Measuring Method

The knob of the gauge touches the work piece and it gives the flatness value at that place. The part top surface was moved all along the knob, and the values differ if the work piece was not flat. Maximum variation was recorded as the degree of deformation (e.g., 0 means perfect flat).

4.4.4 Accumulation underneath the Work piece

The accumulation of the metal takes place after the cutting process underneath the part. Obviously, a perfect cut would not leave any residuals. For better understanding of the system performance, this response was measured for three different areas of the part independently:

a. Straight line

b. Internal curve

c. External curve

Measuring Tool

Similar to roughness response, the available surface roughness (finish) standard mechanisms were not applicable for this response. Instead, a rating system was designed to rate the unwanted accumulations. The rating system scale was between 1 (too much accumulations) and 10 (zero accumulations). For each rate a representative object was defined.

Measuring Method

To measure the amount of accumulation underneath of the three different areas of the part, it was compared to representative objects to find the most similar one. The evaluation was conducted by three researchers and a medium rating was used for the optimization calculations.

4.4.5 Dimensions of the part Responses

The change in the dimensions of the part after the cut was another response that was measured. This was done simply by using an electronic caliper. The measure was for two dimensions in X (length) and Y (width) directions.

Measuring Tool

An electronic caliper with accuracy of 0.001” was used as a tool to measure the dimensions of the fabricated part.

Measuring Method

The part was placed in between the jaws and the actual reading was taken as shown by the caliper.

4.4.6 Bevel Angle Response

The ideal bevel angle, the angle between the surface of the cut edge and the top surface of the part, for a part fabricated by the plasma cutting process was zero. However, it was not always the case. The bevel angle was measured for the internal curve, external curve, and also for the straight line.

4.4.6.1.a Straight Line

In the straight line area of the part, the bevel angle varied in two sides. Therefore, the bevel angle on left side of a straight line and the bevel angle on right side of a straight line were considered as two different responses.

4.4.6.1.b Internal Curve

A single bevel angle for the internal curve was measured for each part.

4.4.6.1.c External Curve

A single bevel angle for the external curve was measured for each part.

4.4.6.2 Measuring Tool

The bevel angles were measured using a protractor with a sliding scale and by keeping the scale parallel to the side. The measuring tool is shown in the Fig 12.

Fig 12. Protractor with a sliding scale

4.4.6.3 Measuring Method

As shown in Fig 12, one edge of the angle measuring apparatus touches the top of the part and its other edge touch the part’s cut edge. Then, bevel angle is read.

4.4.7 Tool Life

According to Coelho et al. (2004), the cutting edge geometry plays a significant role on the insert performance, thus affecting the tool life. The tool life was measured by the number of cuts it had cut. It was included in the responses to identify its correlation with the responses.

4.4.8. Start Point Quality Response

Sometimes the start point of the cutting path was incorrectly passing the part’s boundary and creating a defective part. To identify the causes of this phenomenon, quality of the start point for both internal and external areas of the parts was measured.

4.4.8.1 Measuring Tool

A visual inspection was used for evaluating the quality of the start point. Different objects with diverse defects (from a big deformed hole to no start point) were rated 1 to 10 and used as a comparison scale. One of the pieces is shown in the Fig 13.

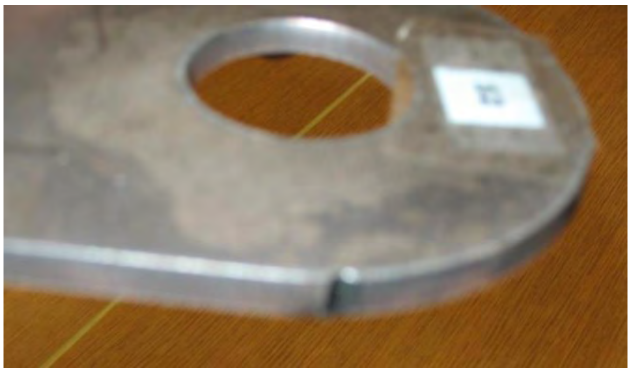

Fig 13. Part used in the comparison scale

4.4.8.2 Measuring Method

The start point quality for the internal and external areas of the part were compared with representing scale objects and rated (1 for a big extra cut and 10 for no start point sign on the part).

4.4.9 Cut Depth

Preliminary experiments showed that the combinations of settings did not always end with a cut (Fig 14). Sometimes a part's boundary was half way cut or not cut at all. By measuring the cut depth as a response for both part's internal and external areas, it was possible to identify the affecting factors for cut depth.

Fig 14. Cut and not cut samples

Measuring Tool

A rating system was used to measure the cut depth. Representative scales were 1 for a minor scratch on the sheet metal's surface to 10 for a complete cut.

Measuring Method

Cut depth for internal and external edges of the part was evaluated and rated based on the status of the cut in those areas.

CHAPTER V

RESULTS

5.1 Mathematical Models

Tool type and cut direction were the two categorical variables which were considered in the design. If the categorical variables were treated as numerical variables then the results would be difficult to interpret or misleading. Therefore, this categorical variable problem was solved by creating dummy variables and the categorical variables were transformed into indicator variables. These indicator variables can take on only two values, either zero or one. The value one indicates the observation belongs in that category, a zero means it does not. In Regression, the indicator variables are used by leaving one of the indicator variables from the Regression model. This indicator variable becomes the base or reference level to which the other levels are compared. If the response value desired is higher, then the indicator variable which gives the higher response value was preferred (Montgomery, 2002).

After conducting all runs of the experiment, the surface quality and geometrical accuracy responses of the fabricated parts were determined. Response Surface Regression was used and the interaction between categorical and numerical variables was neglected as it would become difficult to interpret the results. The data set from the DOE was used to develop an optimization plot, residual plots and mathematical models to show the response behaviors versus the factors. There are two ways to interpret the significant factors and interactions if the factor was not significant and the interaction was significant. They are:

1. Neglecting the interaction effect in the model if the factor was not significant.
2. Including the factor in the model if the interaction effect was significant.

The second approach was used so that the R-squared value was high enough. The factor in the model was included if the interaction effect was significant and the factor effect was not significant.

The Regression analysis was used until the whole model become significant and the regression equation was developed. The resulting models are shown in the appendix B. Mintab 15 software was used to obtain the results and the plots, such as optimization plot, interaction plots, and main effects plot. The P-values were looked at and values which are more than 0.2 were not considered. 80% confidence interval was used in this research as this confidence interval has been used in real life applications (Caleyo et al., 2007, Stanzel et al., 2008, & Azarov et al., 1985). This means that the confidence interval will contain the true mean, 80% of the time. The interaction effects were also taken into account. Then, the equations were developed for all the 18 responses. For the roughness on Internal Curve response, the Regression coefficients and the ANOVA are shown. For the remaining responses, the Regression coefficients and ANOVA are shown in the Appendix. All the Responses and their designations are shown in the following Table 2.

Table 2. The Response table and their desired value

No	Name of the Response	Designation	Target Value
1	Roughness on Internal Curve	R1	10
2	Roughness on External Curve	R2	10
3	Roughness on Straight Line	R3	10
4	Flatness	R4	0
5	Accumulation on Internal Curve	R5	10
6	Accumulation on External Curve	R6	10
7	Accumulation on Straight Line	R7	10
8	Geometrical Accuracy in X-Direction	R8	4.0 in
9	Geometrical Accuracy in y-Direction	R9	6.0 in
10	Tool Life	R10	Max
11	Bevel Angle on Internal Curve	R11	0
12	Bevel Angle on External Curve	R12	0
13	Bevel Angle on Left Side of Straight Line	R13	0
14	Bevel Angle on Right Side of Straight Line	R14	0
15	Start Point Quality for Internal Part	R15	10
16	Start Point Quality for External Part	R16	10
17	Cut Depth Quality for Internal Feature	R17	10
18	Cut Depth Quality for External Feature	R18	10

5.2. Roughness Responses

5.2.1 Roughness on Internal Curve (R1):

The significant factors for this response were identified through Regression analysis. The results are shown below and also in the appendix B.

Table 3. Roughness on Internal Curve Results for 1st iteration

Term	Coef	SE Coef	T	P
Constant	-0.3661	13.5350	-0.027	0.979
A	0.3568	0.2092	1.705	0.102
B	-0.0439	0.3431	-0.128	0.899
C	-0.1028	0.0671	-1.532	0.140
D	15.1636	28.7841	0.527	0.604
F	-0.4454	1.1645	-0.382	0.706
E_1	-0.5707	0.6205	-0.920	0.368
E_2	-0.6880	0.5218	-1.319	0.201
G_0	-0.8133	0.4374	-1.859	0.076
A*A	-0.0012	0.0013	-0.951	0.352
B*B	0.0006	0.0023	0.254	0.802
C*C	-0.0007	0.0003	-2.868	0.009
D*D	-22.3910	49.3232	0.454	0.654
F*F	0.0894	0.1318	0.678	0.505
A*B	-0.0022	0.0013	-1.729	0.098
A*C	0.0002	0.0005	0.433	0.669

A*D	-0.1930	0.2489	-0.776	0.446
A*F	-0.0034	0.0133	-0.255	0.801
B*C	0.0021	0.0006	3.228	0.004
B*D	0.0499	0.2955	0.169	0.867
B*F	-0.0051	0.0157	-0.324	0.749
C*D	0.1539	0.1262	1.220	0.235
C*F	0.0015	0.0056	0.265	0.794
D*F	1.9858	1.8298	1.085	0.290

Table 3. Roughness on Internal Curve Results for 1st iteration continued

S = 1.29592   PRESS = 235.367

R-Sq = 77.52% R-Sq(pred) = 0.00% R-Sq(adj) = 54.02%

Table 4. ANOVA for Roughness on Internal Curve 1st iteration

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	127.423	127.4228	5.54012	3.30	0.003
Linear	8	90.573	19.5760	2.44700	1.46	0.229
Square	5	11.547	16.7318	3.34635	1.99	0.120
Interaction	10	25.303	25.3031	2.53031	1.51	0.203
Residual Error	22	36.947	36.9468	1.67940	*	
Lack-of-Fit	21	36.947	36.9468	1.75937	*	
Pure Error	1	0.000	0.0000	0.00000		
Total	45	164.370				

With 80% confidence interval the significant factors were identified

The regression equation is

$$R1 = 7.89 + 0.0726\,A - 0.0424\,B - 0.0456\,C + 2.93\,D - 0.253\,E\_2 - 0.718\,G\_0 - 0.000849\,C*C - 0.00096\,A*B + 0.00193\,B*C + 0.0828\,C*D$$

Table 5. Roughness on Internal Curve Results for 2nd iteration

Predictor	Coef	SE Coef	T	P
Constant	7.893	4.951	1.59	0.119
A	0.07259	0.07665	0.95	0.349
B	-0.04243	0.06759	-0.63	0.534
C	-0.04558	0.04550	-1.00	0.322
D	2.929	3.789	0.77	0.444
E_2	-0.2533	0.4248	-0.60	0.554
G_0	-0.7183	0.3863	-1.86	0.070
C*C	-0.0008494	0.0002259	-3.76	0.001
A*B	-0.000961	0.001027	-0.94	0.355
B*C	0.0019292	0.0005436	3.55	0.001
C*D	0.08283	0.09380	0.88	0.382

S = 1.34497   R-Sq = 67.3%   R-Sq(adj) = 59.3%

Analysis of Variance

Table 6. ANOVA for Roughness on Internal Curve 2nd iteration

Source	DF	SS	MS	F	P
Regression	10	152.660	15.266	8.44	0.000
Residual Error	41	74.167	1.809		
Total	51	226.827			

Then, again the significant factors were identified and the Regression model was developed.

Estimated Regression Coefficients for R1

The Regression equation is

$$R1 = 7.89 + 0.0726\,A - 0.0424\,B - 0.0456\,C + 2.93\,D - 0.253\,E\_2 - 0.718\,G\_0 - 0.000849\,C*C - 0.00096\,A*B + 0.00193\,B*C + 0.0828\,C*D$$

Table 7. Roughness on Internal Curve Results for 3rd iteration

Predictor	Coef	SE Coef	T	P
Constant	7.893	4.951	1.59	0.119
A	0.07259	0.07665	0.95	0.349
B	-0.04243	0.06759	-0.63	0.534
C	-0.04558	0.04550	-1.00	0.322
D	2.929	3.789	0.77	0.444
E_2	-0.2533	0.4248	-0.60	0.554
G_0	-0.7183	0.3863	-1.86	0.070
C*C	-0.0008494	0.0002259	-3.76	0.001
A*B	-0.000961	0.001027	-0.94	0.355
B*C	0.0019292	0.0005436	0.355	0.001
C*D	0.08283	0.09380	0.88	0.382

S = 1.34497   R-Sq = 67.3%   R-Sq(adj) = 59.3%

Analysis of Variance

Table 8. ANOVA for Roughness on Internal Curve 3rd iteration

Source	DF	SS	MS	F	P
Regression	10	152.660	15.266	8.44	0.000
Residual Error	41	74.167	1.809		
Total	51	226.827			

Then again Regression analysis was developed with the significant factors. The Regression analysis with the significant factors was

The Regression analysis was developed again.

The Regression equation is

$$R1 = 12.8 - 0.101\,B - 0.0209\,C - 0.896\,G\_0 - 0.000817\,C*C + 0.00185\,B*C$$

Table 9. Roughness on Internal Curve Results for 4th iteration

Predictor	Coef	SE Coef	T	P
Constant	12.830	1.872	6.85	0.000
B	-0.10056	0.02514	-4.00	0.000
C	-0.02094	0.04065	-0.52	0.609
G_0	-0.8964	0.3794	-2.36	0.022
C*C	-0.0008168	0.0002236	-3.65	0.001
B*C	0.0018476	0.0005322	3.47	0.001

S = 1.36142 R-Sq = 62.4% R-Sq(adj) = 58.3%

Table 10. ANOVA for Roughness on Internal Curve 4th iteration

Source	DF	SS	MS	F	P
Regression	5	141.568	28.314	15.28	0.000
Residual Error	46	85.259	1.853		
Total	51	226.827			

So the whole model was significant and the significant factors are pressure, cut speed, cut direction, cut speed² and interaction between pressure and cut speed.

In this way all the statistical significant factors for all the responses were determined.

5.2.2 Roughness on External Curve (R2):

The significant factors were pressure, cut speed, tool type, cut direction, cut speed², and interaction between pressure and cut speed. The results were shown in the appendix B.

The Regression equation is

$$R2 = 11.3 - 0.0626\,B + 0.0141\,C - 0.927\,E\_1 - 1.15\,G\_0 - 0.000624\,C * C + 0.00112\,B * C$$

5.2.3 Roughness on Straight Line (R3):

The significant factors were cut speed, torch height, cut speed² and interaction between cut speed and torch height. The results were shown in the appendix B.

The Regression equation is

$$R3 = 3.83 + 0.105\,C + 15.5\,D - 0.000458\,C * C - 0.189\,C * D$$

5.3. Flatness (R4):

The significant factor affecting this response was tool type. The results were shown in the appendix B.

The Regression equation is

$$R4 = 0.0235 + 0.00897\,E\_1$$

5.4. Accumulation Responses

5.4.1 Accumulation on Internal Curve (R5):

The significant factors were cut speed, tool type and cut speed². The results were shown in the appendix B.

The Regression equation is

$$R5 = 2.05 + 0.182\,C + 0.902\,E\_1 + 1.09\,E\_2 - 0.00119\,C * C$$

5.4.2 Accumulation on External Curve (R6):

The significant factors were pressure, cut speed, slower on curves, tool type, cut speed² and the interaction between pressure and slower on curves. The results were shown in the appendix B.

The Regression equation is

$$R6 = -1.01 + 0.0403\,B + 0.200\,C + 1.69\,F + 1.21\,E\_2 - 0.00133\,C * C - 0.0234\,B * F$$

5.4.3 Accumulation on Straight Line (R7):

The significant factors affecting accumulation on straight line were cut speed, cut speed². The results were shown in the appendix B.

The Regression equation is

$$R7 = 2.72 + 0.189\,C - 0.00129\,C * C$$

5.5. Dimensional Reponses

5.5.1 Geometry in X-Direction (R8):

The significant factors affecting Geometry in X-Direction were cut speed, torch height, slower on curves, tool type and interaction between cut speed and torch height and in between cut speed and slower on curves. The results were shown in the appendix B.

The Regression equation is

$$R8 = 4.05 - 0.000533\,C - 0.283\,D - 0.00280\,F - 0.0210\,E\_1 + 0.0114\,E\_2 + 0.00305\,C*D + 0.000086\,C*F$$

5.5.2 Geometry in Y-Direction (R9):

The significant factors affecting this response were current, torch height, cut direction, current^2, and torch height^2. The results were shown in the appendix B.

The Regression equation is

$$R9 = 6.71 - 0.0241\,A - 1.07\,D + 0.0448\,G\_0 + 0.000200\,A*A + 2.62\,D*D$$

5.6 Tool Life (R10):

Tool life is not a function of the factors. It was considered in the responses to identify its correlation with other responses. As shown in Table 11, most of the correlations are low and non-significant (i.e., increasing tool life decreases the part quality), however because tools (tips) were replaced before they get worn, their effects on the value of other responses are not significant.

Table 11 . Correlation between R10 (tool life) vs. other responses.

	R1	R2	R3	R4	R5	R6	R7	R8
R10	**0.15**	**-0.02**	**0.07**	**-0.06**	**-0.18**	**-0.16**	**-0.15**	**-0.1**

	R9	R10	R11	R12	R13	R14	R15	R16
R10	**0.1**	**1**	**0.05**	**-0.06**	**-0.1**	**0.03**	**-0.05**	**0.02**

5.7. Bevel Angle Responses

5.7.1 Bevel angle on Internal Curve (R11):

The significant factors affecting bevel angle on internal curve were current, pressure, cut speed, Torch height, slower on curves and interactions between current and pressure, current and cut speed, current and torch height, current and slower on curves, and pressure and slower on curves. The results were shown in the appendix B.

The Regression equation is

$$R11 = -80.4 + 1.60\,A + 0.667\,B - 0.259\,C - 4.91\,F + 149\,D - 0.0165\,A * B + 0.00635\,A * C - 2.17\,A * D - 0.0917\,A * F + 0.161\,B * F$$

5.7.2 Bevel Angle on External Curve (R12):

The significant factors affecting this response were current, pressure, torch height, slower on curves and interaction effect between current and torch height and in between pressure and slower on curves. The results were shown in the appendix B.

The Regression equation is

$$R12 = -16.8 + 0.614\, A - 0.458\, B + 211\, D - 11.4\, F - 2.35\, A * D + 0.164\, B * F$$

5.7.3 Bevel Angle on Left Side of Straight Line (R13):

The significant factors affecting this response were torch height, tool type, and torch height^2. The results were shown in the appendix B.

The Regression equation is

$$R13 = -24.4 + 239\, D - 3.98\, E\_1 - 552\, D * D$$

5.7.4 Bevel Angle on Right Side of Straight Line (R14):

The significant factors affecting this response were current, pressure, cut speed, tool type, cut speed^2, and interaction between current and pressure and in between current and cut speed. The results were shown in the appendix B.

The Regression equation is

$$R14 = -28.1 + 0.446\, A + 0.638\, B - 0.353\, C + 11.4\, E\_1 - 0.0103\, A * B + 0.00629\, A * C$$

5.8. Start Point Quality Responses

5.8.1 Start Point Quality for Internal Part (R15):

The significant factors affecting this response were pressure, cut speed, slower on curves, tool type, cut speed² and interaction between pressure and slower on curves and in between pressure and slower on curves. The results were shown in the appendix B.

The Regression equation is

$$R15 = 9.85 - 0.0287\,B - 0.0197\,C + 0.867\,F - 0.679\,E\_1 - 0.000283\,C*C + 0.000871\,B*C - 0.0114\,B*F$$

5.8.2 Start Point Quality for External Part (R16):

The significant factors affecting this response were torch height, slower on curves, cut speed, pressure, tool type, cut direction, cut speed², and interaction between pressure and cut speed, pressure and torch height, and cut speed and slower on curves. The results were shown in the appendix B.

The Regression equation is

$$R16 = 17.5 - 26.9\,D - 0.178\,F - 0.0244\,C - 0.149\,B - 0.795\,E\_1 - 1.39\,G\_0 - 0.000601\,C*C + 0.00123\,B*C + 0.433\,B*D + 0.00526\,C*F$$

5.9 Cut Depth Responses

Among the 89 fabricated parts, some of the parts were not fully cut and they were not extracted from the sheet metal. While those parts are missing data for other responses, they are usable data for cut depth responses. Also, as mentioned before, a rating system was used to measure cut depth. In this response, a value of 10 (maximum quality) was given to those parts which were cut and the remaining parts which did not cut were rated with lower numbers (1-10). Since, of all the parts, 53 were cut and 36 were not cut, in the Desirability function, due to unequal length of columns, these two responses are separated. The Regression models are independently developed to identify the significant factors and their effects on these two responses.

5.9.1 Cut Depth Quality for Internal Feature (R17):

The factors affecting this response were current, pressure, cut speed, torch height, tool type, and slower on curves. The results were shown in the appendix B.

$$R17 = 6.73 + 0.0596\,A - 0.0368\,B - 0.0363\,C + 6.87\,D + 0.883\,E\_1 + 0.814\,E\_2 + 0.315\,F$$

5.9.2 Cut Depth Quality for External Part (R18):

The factors affecting this response were current, pressure, cut speed and torch height. The results were shown in the appendix B.

$$R18 = 7.63 + 0.0728\,A - 0.0421\,B - 0.0485\,C + 6.93\,D$$

The responses which were affected by the factors are shown in Fig 15.

Fig 15. Figure showing which factors affect which responses

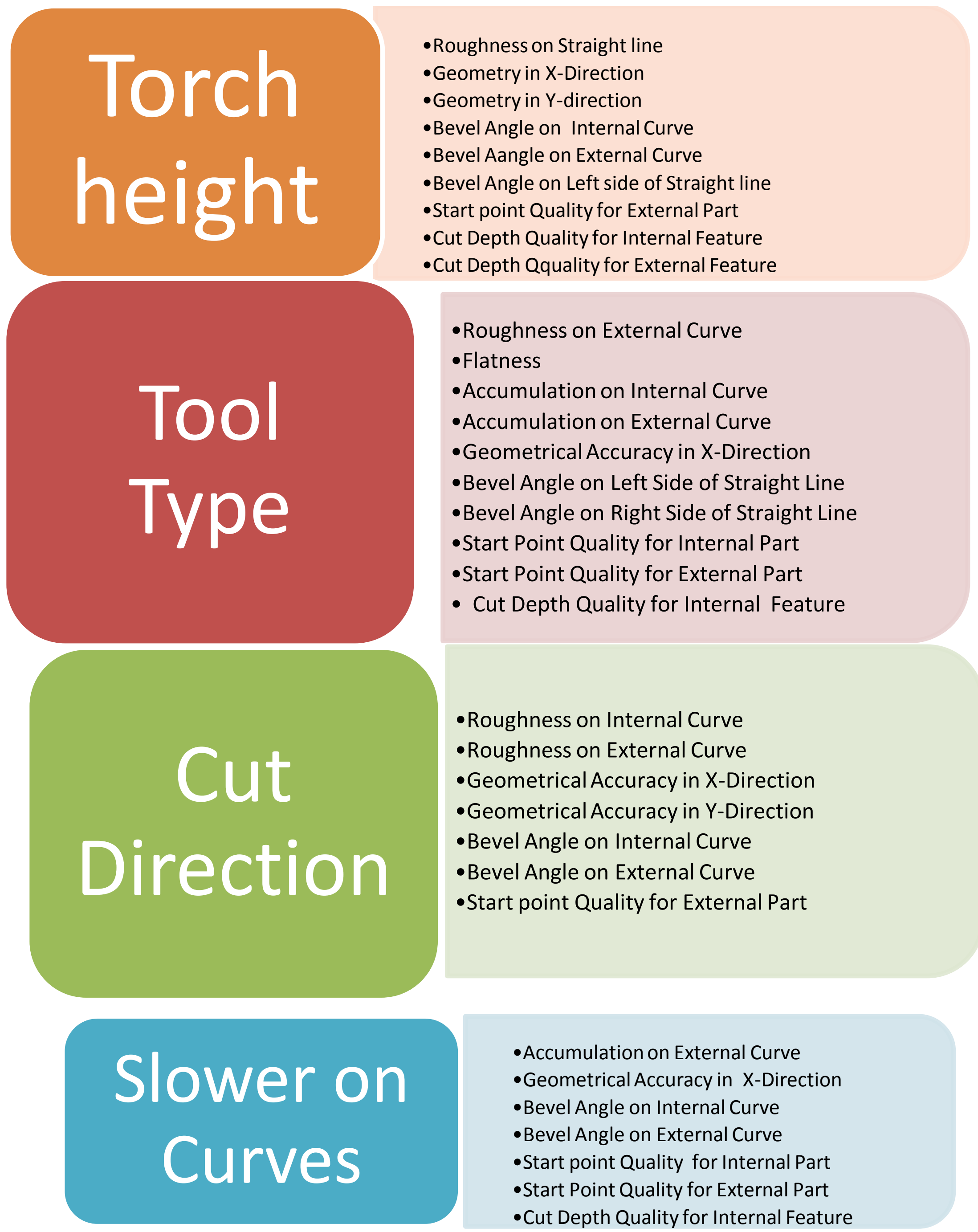

Fig 15. Figure showing which factors affect which responses continued

5.10 Desirability Function

Tradeoffs between the responses were observed during analyzing the mathematical models. Choosing a factor and increasing its value have an impact on one or more responses and it did not have an impact on the other responses. Therefore, for balancing the tradeoffs, a multi-response optimization technique was used. Derringer and Suich (1980) suggested a technique for this kind of approaches. They called it Desirability Function, a method that was used for tradeoff balance for the responses.

The Desirability Function in this research was developed using Minitab software. In this Desirability Function, different importance weights were given to different responses: An importance of 4 for roughness and accumulation responses, 3 for bevel angle responses, 2 for start point quality responses and part geometry responses, and 1 for tool life and flatness.

For roughness, accumulation, start point quality, tool life, and cut depth quality responses the goal of 10 as maximum was chosen. For part geometry and bevel angle the goal was to target (equal to CAD file dimensions). We chose the goal for flatness as 0. The results were shown below.

After incorporating all the above values, the responses and their Desirability values are given below.

R1 = 9.3898 , *Desirability = 0.932197*

R2 = 9.7443 , *Desirability = 0.971590*

R3 = 10.0138 , *Desirability = 1.000000*

R4 = 0.0181 , *Desirability = 0.892339*

R5 = 9.9990 , Desirability = 0.999888

R6 = 10.6272 , Desirability = 1.000000

R7 = 10.5197 , Desirability = 1.000000

R8 = 3.9814 , Desirability = 0.854725

R9 = 6.0002 , Desirability = 0.994658

R11 = 4.5917 , Desirability = 0.826730

R12 = 1.8111 , Desirability = 0.922932

R13 = -5.3500 , Desirability = 0.827420

R14 = 2.5416 , Desirability = 0.924133

R16 = 9.8297 , Desirability = 0.981073

Composite Desirability = 0.944416

The responses R11 to R15 were Bevel Angle responses and the target value for the Bevel Angle is zero. The Desirability Function gives the value which is slightly less or more than the target value. The difference between the target value and the desired value is almost equal and the difference is non-significant. So, the desirable value was good enough.

5.10.1 Desirability for Cut Depth Quality Response:

As explained in the previous section, the Desirability Function for these two cut depth responses were separately conducted as below.

$$R17 = 9.72 \ , \ desirability = 0.97$$

$$R18 = 9.67 \ , \ desirability = 1.00$$

Based on the Desirability Function, overall optimum point was reached in the following setting:

Optimization Plot

$$\begin{pmatrix} Current \\ Pressure \\ Cut\ Speed \\ Torch\ height \\ Slower\ on\ Curves \\ Tool\ Type \\ Cut\ Direction \end{pmatrix} = \begin{pmatrix} 80 \\ 90 \\ 54.55 \\ 0.297 \\ 0.3636 \\ C \\ Horizontal \end{pmatrix} \longrightarrow$$

Optimal Parameter Setting

The optimization plot was plotted to show the effect of each factor (columns) on the responses or composite Desirability (rows). The vertical red lines on the graph represent the current factor settings. The numbers displayed at the top of a column show the current factor level settings (in red). The horizontal blue lines and numbers represent the responses for the current factor level. The optimization plot was shown in the appendix C.

Residuals Plot

Histogram of residuals**:** An exploratory tool to show general characteristics of the data, including:

– Typical values, spread or variation, and shape

– Unusual values in the data

Long tails in the plot may indicate skewness in the data. If one or two bars are far from the others, those points may be outliers. Because the appearance of the histogram changes depending on the number of intervals used to group the data, the normal probability plot and goodness-of-fit tests are used to assess the normality of the residuals.

Normal probability plot of Residuals: The points in this plot should generally form a straight line if the residuals are normally distributed. If the points on the plot depart from a straight line, the normality assumption may be invalid which could cause the true significance level and the power to differ slightly from the reported values, with the power generally being lower. In this study, only the normal probability plot for the response named Geometrical Accuracy in Y-Direction is not normal.

Residuals versus Fits**:** This plot shows a random pattern of residuals on both sides of 0. If a point lies far from the majority of points, it may be an outlier. Also, in the residual plot there should not be any recognizable patterns.

Residuals versus order**:** This is a plot of all residuals in the order that the data was collected and can be used to find non-random error, especially of time-related effects. A positive correlation is indicated by a clustering of residuals with the same sign. A negative correlation is indicated by rapid changes in the signs of consecutive residuals.

All the four of the plots for all the 18 responses were shown in the appendix D.

The iterative procedure of the Response Surface Design is stopped at one iteration as the results were satisfactory.

5.11 Validation

To validate the Optimal Parameter Setting, 10 parts were built at that setting and box plots were plotted to verify whether they contained the desired values inputted in the Desirability Function step.

Boxplots, graphical summary of the distribution of a sample that shows its shape, central tendency, and variability, are used to show the ranges in which the response values fall. Boxplots are also useful for comparing several distributions.

The box plots for the 18 responses are shown in the Appendix E. As all the parts were cut, the Cut Depth responses (R17 and R18) have the constant value of 10 and the resulting boxplot is a straight line.

The boxplots show that the resulting values when using the Optimal Parameter Settings are near the desired values. Thus, the Optimal Parameter Setting -is good to produce desirable parts.

CHAPTER VI

CONCLUSIONS AND FUTURE RESEARCH

Conclusion

In this research, the optimum parameter settings were identified for the automated plasma cutting process by doing $3^6 * 2^1$ experiments with 2 replicates and reduced the number of runs with an Orthogonal Array approach. Seven independent variables were considered for the study. Six of them were studied at three levels while the seventh independent variable, cut direction, was studied only at two levels (Horizontal and Vertical Direction). Seven affecting factors and eighteen responses make the automated plasma cutting process very complex. Without applying design of experiment it seems impossible or very difficult to perform all the runs. The entire process in this study was conducted for stainless steel sheet metal with 0.25 inch thickness.

After performing the Design of Experiments, Regression analysis was conducted to identify the significant factors affecting each response. Several mathematical models to explain each one of the responses was obtained. Then, a Desirability Function, a multi-response optimization technique, was used to combine the models obtained for each response and balance the trade-offs between the responses. Response Surface technique permitted the identification of parameter settings that optimize the resulting quality characteristics. Through experimentation, validation was again performed on the optimum parameter setting before coming to a conclusion. Finally, the independent variables which influence the most the response variable outcomes were identified.

Looking upon the results, one can conclude that the effect of torch height, tool type and cut direction plays a vital role in surface quality characteristics. So, for a better cut quality one should consider these factors and proceed. The effect of factors on the responses was shown diagrammatically in Fig 15.

6.1 Future Research

A similar study can be done to investigate other popular sheet metal thicknesses. Also, that would be interesting (and costly) if one can conduct a new similar study by incorporating sheet metal thickness as one of the factors. So, one could take this in to consideration and make a related study.

As many of the responses measured were qualitative, one can use new measuring equipment and measure the responses quantitative and can make a similar study. Another study can also be made using other materials such as wood etc.

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APPENDIX

Appendix A

Run No.	Current	Pressure	Cut speed	Torch Height	Tool Type	Slower on Curves	Cut Direction
1	80	60	10	0.1	b	2	0
2	60	75	55	0.2	b	0	1
3	40	90	55	0.2	b	2	0
4	60	90	100	0.2	c	0	0
5	60	60	55	0.2	a	0	1
6	60	75	10	0.2	c	4	0
7	40	75	10	0.2	b	2	1
8	80	90	55	0.1	b	4	0
9	40	75	100	0.2	a	4	1
10	80	75	55	0.2	c	4	1
11	80	75	100	0.3	b	0	0
12	80	75	55	0.3	b	2	0
13	40	90	100	0.2	a	2	0
14	40	90	10	0.3	c	0	1
15	80	90	10	0.3	a	2	0
16	60	75	10	0.1	b	4	1
17	40	60	10	0.1	a	0	1
18	60	60	55	0.3	c	2	0
19	60	75	55	0.2	c	2	1
20	40	60	100	0.1	a	2	1
21	60	90	10	0.2	a	2	1
22	80	60	100	0.3	b	2	0
23	40	75	55	0.2	c	0	1
24	40	75	10	0.1	c	4	0
25	60	75	100	0.1	c	4	0
26	60	75	10	0.1	a	0	0
27	40	60	55	0.3	b	0	1
28	80	75	10	0.3	a	0	1
29	80	75	55	0.2	c	0	0
30	40	75	100	0.3	b	4	0
31	40	90	55	0.1	c	2	0
32	80	75	100	0.1	b	2	1
33	80	90	55	0.2	a	4	0

34	60	60	55	0.3	b	4	0
35	60	90	100	0.1	b	0	1
36	60	60	100	0.2	c	4	0
37	80	90	100	0.2	c	2	1
38	40	60	100	0.2	b	0	1
39	80	75	100	0.3	c	4	1
40	40	90	100	0.1	c	4	1
41	80	60	100	0.2	a	0	0
42	60	60	100	0.3	a	0	1
43	80	90	55	0.3	c	4	0
44	40	60	10	0.3	c	4	1
45	40	60	55	0.3	a	4	0
46	60	75	10	0.1	a	0	0
47	60	90	10	0.1	b	2	0
48	60	60	100	0.1	c	2	1
49	60	90	55	0.1	c	4	1
50	80	75	100	0.3	a	4	0
51	80	75	10	0.2	c	0	1
52	80	60	55	0.3	c	0	1
53	80	90	10	0.2	b	0	0
54	60	60	10	0.3	b	2	1
55	60	60	10	0.1	a	4	0
56	40	90	55	0.3	a	4	1
57	40	90	55	0.2	a	0	1
58	80	90	10	0.1	c	0	0
59	40	75	100	0.2	c	2	0
60	60	90	10	0.3	a	4	0
61	80	60	10	0.3	c	2	1
62	40	75	100	0.1	b	0	0
63	60	75	100	0.2	a	2	0
64	60	75	10	0.3	a	2	1
65	80	60	55	0.3	a	2	1
66	60	60	55	0.1	b	0	0
67	40	60	55	0.1	b	2	1
68	40	60	10	0.2	c	2	0
69	40	75	100	0.3	a	2	1
70	80	75	55	0.1	a	0	1
71	60	90	55	0.3	a	0	0
72	40	75	100	0.1	b	0	0
73	80	90	10	0.1	a	4	1
74	60	90	55	0.1	a	2	1
75	80	90	100	0.3	a	0	1
76	80	60	100	0.1	b	4	1
77	80	90	10	0.3	b	4	1
78	40	60	100	0.1	c	0	0
79	40	60	10	0.2	b	4	0

80	80	60	55	0.2	b	2	1
81	80	60	10	0.2	a	4	1
82	80	90	55	0.1	c	2	1
83	60	60	10	0.3	c	0	0
84	60	90	100	0.2	b	4	1
85	60	90	100	0.3	c	2	1
86	80	75	100	0.2	b	4	0
87	40	75	55	0.2	a	2	0
88	80	60	55	0.1	c	4	0
89	80	60	110	0.3	c	2	1

Appendix B

Response Surface Regression: R1 versus A, B, C, D, F, E_1, E_2, G_0

```
The analysis was done using uncoded units.

Estimated Regression Coefficients for R1

Term           Coef  SE Coef       T      P
Constant    -0.3661  13.5350  -0.027  0.979
A            0.3568   0.2092   1.705  0.102
B           -0.0439   0.3431  -0.128  0.899
C           -0.1028   0.0671  -1.532  0.140
D           15.1636  28.7841   0.527  0.604
F           -0.4454   1.1645  -0.382  0.706
E_1         -0.5707   0.6205  -0.920  0.368
E_2         -0.6880   0.5218  -1.319  0.201
G_0         -0.8133   0.4374  -1.859  0.076
A*A         -0.0012   0.0013  -0.951  0.352
B*B          0.0006   0.0023   0.254  0.802
C*C         -0.0007   0.0003  -2.868  0.009
D*D        -22.3910  49.3232  -0.454  0.654
F*F          0.0894   0.1318   0.678  0.505
A*B         -0.0022   0.0013  -1.729  0.098
A*C          0.0002   0.0005   0.433  0.669
A*D         -0.1930   0.2489  -0.776  0.446
A*F         -0.0034   0.0133  -0.255  0.801
B*C          0.0021   0.0006   3.228  0.004
B*D          0.0499   0.2955   0.169  0.867
B*F         -0.0051   0.0157  -0.324  0.749
C*D          0.1539   0.1262   1.220  0.235
C*F          0.0015   0.0056   0.265  0.794
D*F          1.9858   1.8298   1.085  0.290


S = 1.29592    PRESS = 235.367
R-Sq = 77.52%  R-Sq(pred) = 0.00%  R-Sq(adj) = 54.02%


Analysis of Variance for R1

Source          DF   Seq SS    Adj SS   Adj MS     F      P
Regression      23  127.423  127.4228  5.54012  3.30  0.003
  Linear         8   90.573   19.5760  2.44700  1.46  0.229
  Square         5   11.547   16.7318  3.34635  1.99  0.120
```

Interaction	10	25.303	25.3031	2.53031	1.51	0.203
Residual Error	22	36.947	36.9468	1.67940		
Lack-of-Fit	21	36.947	36.9468	1.75937	*	*
Pure Error	1	0.000	0.0000	0.00000		
Total	45	164.370				

Unusual Observations for R1

Obs	StdOrder	R1	Fit	SE Fit	Residual	St Resid
14	14	9.000	7.660	1.177	1.340	2.47 R
55	55	8.000	6.080	0.874	1.920	2.01 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R2 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R2

Term	Coef	SE Coef	T	P
Constant	19.7127	15.2462	1.293	0.209
A	0.0779	0.2356	0.331	0.744
B	-0.3910	0.3864	-1.012	0.323
C	0.0199	0.0756	0.264	0.794
D	8.3489	32.4233	0.257	0.799
F	-1.2966	1.3118	-0.988	0.334
E_1	-1.0440	0.6989	-1.494	0.149
E_2	-0.2184	0.5877	-0.372	0.714
G_0	-0.9825	0.4927	-1.994	0.059
A*A	-0.0003	0.0015	-0.184	0.856
B*B	0.0026	0.0026	0.997	0.330
C*C	-0.0005	0.0003	-1.532	0.140
D*D	4.7136	55.5592	0.085	0.933
F*F	0.1455	0.1485	0.980	0.338
A*B	-0.0008	0.0014	-0.568	0.576
A*C	-0.0000	0.0006	-0.040	0.969
A*D	0.0438	0.2804	0.156	0.877
A*F	0.0037	0.0149	0.245	0.809
B*C	0.0011	0.0007	1.592	0.126
B*D	-0.0296	0.3328	-0.089	0.930
B*F	0.0057	0.0177	0.322	0.750
C*D	-0.1186	0.1421	-0.835	0.413
C*F	-0.0025	0.0064	-0.401	0.692
D*F	0.6033	2.0612	0.293	0.773

S = 1.45976   PRESS = 203.873
R-Sq = 73.34% R-Sq(pred) = 0.00% R-Sq(adj) = 45.46%

Analysis of Variance for R2

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	128.946	128.946	5.6064	2.63	0.013
Linear	8	107.100	15.514	1.9393	0.91	0.526
Square	5	13.770	9.067	1.8135	0.85	0.529
Interaction	10	8.076	8.076	0.8076	0.38	0.943
Residual Error	22	46.880	46.880	2.1309		
Lack-of-Fit	21	28.880	28.880	1.3752	0.08	0.998

Pure Error	1	18.000	18.000	18.0000	
Total	45	175.826			

Unusual Observations for R2

Obs	StdOrder	R2	Fit	SE Fit	Residual	St Resid
46	46	1.000	4.719	0.829	-3.719	-3.10 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R3 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R3

Term	Coef	SE Coef	T	P
Constant	16.6474	13.5689	1.227	0.233
A	-0.0402	0.2097	-0.192	0.850
B	-0.2696	0.3439	-0.784	0.442
C	0.0867	0.0673	1.289	0.211
D	9.6763	28.8563	0.335	0.741
F	-0.3874	1.1674	-0.332	0.743
E_1	-0.5122	0.6220	-0.823	0.419
E_2	-0.3742	0.5231	-0.715	0.482
G_0	-0.6533	0.4385	-1.490	0.150
A*A	0.0003	0.0013	0.198	0.845
B*B	0.0021	0.0023	0.908	0.374
C*C	-0.0003	0.0003	-1.233	0.230
D*D	33.1745	49.4469	0.671	0.509
F*F	0.0467	0.1322	0.354	0.727
A*B	0.0001	0.0013	0.081	0.936
A*C	-0.0002	0.0005	-0.451	0.656
A*D	-0.0183	0.2495	-0.073	0.942
A*F	0.0058	0.0133	0.437	0.666
B*C	0.0003	0.0006	0.470	0.643
B*D	-0.1852	0.2962	-0.625	0.538
B*F	-0.0064	0.0157	-0.408	0.687
C*D	-0.1723	0.1265	-1.362	0.187
C*F	-0.0038	0.0057	-0.666	0.513
D*F	1.8234	1.8344	0.994	0.331

S = 1.29917 PRESS = 203.378
R-Sq = 64.62% R-Sq(pred) = 0.00% R-Sq(adj) = 27.63%

Analysis of Variance for R3

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	67.824	67.824	2.9489	1.75	0.098
Linear	8	47.037	8.874	1.1092	0.66	0.722
Square	5	12.568	5.435	1.0870	0.64	0.669
Interaction	10	8.219	8.219	0.8219	0.49	0.881
Residual Error	22	37.132	37.132	1.6878		
Lack-of-Fit	21	35.132	35.132	1.6730	0.84	0.713
Pure Error	1	2.000	2.000	2.0000		
Total	45	104.957				

Unusual Observations for R3

Obs	StdOrder	R3	Fit	SE Fit	Residual	St Resid	
1	1	5.000	6.473	1.135	-1.473	-2.33	R
24	24	4.000	6.071	0.981	-2.071	-2.43	R
75	75	8.000	9.639	1.037	-1.639	-2.09	R
86	86	6.000	7.971	0.963	-1.971	-2.26	R

R denotes an observation with a large standardized residual.

Response Surface Regression: R4 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R4

Term	Coef	SE Coef	T	P
Constant	-0.003722	0.128408	-0.029	0.977
A	-0.001085	0.001985	-0.547	0.590
B	0.001867	0.003255	0.574	0.572
C	0.000044	0.000637	0.070	0.945
D	0.001387	0.273077	0.005	0.996
F	-0.006305	0.011048	-0.571	0.574
E_1	0.009098	0.005886	1.546	0.136
E_2	0.002586	0.004950	0.522	0.607
G_0	0.003775	0.004150	0.910	0.373
A*A	0.000002	0.000012	0.168	0.868
B*B	-0.000005	0.000022	-0.247	0.807
C*C	0.000002	0.000002	0.678	0.505
D*D	0.060017	0.467933	0.128	0.899
F*F	0.000866	0.001251	0.692	0.496
A*B	-0.000002	0.000012	-0.196	0.847
A*C	-0.000001	0.000005	-0.225	0.824
A*D	0.003047	0.002361	1.290	0.210
A*F	0.000148	0.000126	1.176	0.252
B*C	-0.000002	0.000006	-0.273	0.787
B*D	-0.003401	0.002803	-1.213	0.238
B*F	-0.000090	0.000149	-0.608	0.549
C*D	0.000056	0.001197	0.046	0.963
C*F	-0.000042	0.000053	-0.777	0.446
D*F	0.004127	0.017360	0.238	0.814

S = 0.0122945 PRESS = 0.0144025
R-Sq = 42.06% R-Sq(pred) = 0.00% R-Sq(adj) = 0.00%

Analysis of Variance for R4

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	0.002414	0.002414	0.000105	0.69	0.804
Linear	8	0.001622	0.000693	0.000087	0.57	0.789
Square	5	0.000215	0.000164	0.000033	0.22	0.951
Interaction	10	0.000577	0.000577	0.000058	0.38	0.942
Residual Error	22	0.003325	0.003325	0.000151		
Lack-of-Fit	21	0.002379	0.002379	0.000113	0.12	0.991
Pure Error	1	0.000946	0.000946	0.000946		
Total	45	0.005740				

Unusual Observations for R4

Obs	StdOrder	R4	Fit	SE Fit	Residual	St Resid
46	46	0.072	0.043	0.007	0.029	2.91 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R5 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R5

Term	Coef	SE Coef	T	P
Constant	2.4512	16.8102	0.146	0.885
A	0.1615	0.2598	0.621	0.541
B	-0.0220	0.4261	-0.052	0.959
C	0.1334	0.0833	1.601	0.124
D	-36.4320	35.7494	-1.019	0.319
F	0.5140	1.4463	0.355	0.726
E_1	0.9991	0.7706	1.296	0.208
E_2	0.9833	0.6480	1.517	0.143
G_0	0.1184	0.5432	0.218	0.830
A*A	-0.0012	0.0016	-0.770	0.449
B*B	0.0002	0.0029	0.062	0.951
C*C	-0.0013	0.0003	-3.919	0.001
D*D	-8.7208	61.2585	-0.142	0.888
F*F	0.0003	0.1637	0.002	0.999
A*B	-0.0005	0.0016	-0.336	0.740
A*C	0.0001	0.0006	0.168	0.868
A*D	0.2130	0.3091	0.689	0.498
A*F	-0.0035	0.0165	-0.213	0.834
B*C	0.0001	0.0008	0.165	0.871
B*D	0.2510	0.3670	0.684	0.501
B*F	-0.0121	0.0195	-0.621	0.541
C*D	0.0995	0.1567	0.635	0.532
C*F	0.0076	0.0070	1.079	0.292
D*F	1.0616	2.2726	0.467	0.645

S = 1.60950   PRESS = 310.290
R-Sq = 82.04% R-Sq(pred) = 2.19% R-Sq(adj) = 63.25%

Analysis of Variance for R5

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	260.248	260.2480	11.31513	4.37	0.000
Linear	8	196.391	27.9203	3.49004	1.35	0.273
Square	5	50.585	41.1090	8.22180	3.17	0.026
Interaction	10	13.272	13.2724	1.32724	0.51	0.863
Residual Error	22	56.991	56.9911	2.59051		
Lack-of-Fit	21	56.991	56.9911	2.71386	*	*
Pure Error	1	0.000	0.0000	0.00000		
Total	45	317.239				

Unusual Observations for R5

Obs	StdOrder	R5	Fit	SE Fit	Residual	St Resid
47	47	3.000	5.444	1.246	-2.444	-2.40 R
51	51	1.000	4.682	1.002	-3.682	-2.92 R

```
 53        53  9.000  6.032   1.277     2.968      3.03 R

R denotes an observation with a large standardized residual.
```

Response Surface Regression: R6 versus A, B, C, D, F, E_1, E_2, G_0

```
The analysis was done using uncoded units.

Estimated Regression Coefficients for R6

Term          Coef  SE Coef       T      P
Constant  -10.8155  21.3437  -0.507  0.617
A           0.1662   0.3299   0.504  0.619
B           0.1344   0.5410   0.248  0.806
C           0.1350   0.1058   1.276  0.215
D          16.7389  45.3904   0.369  0.716
F           2.8062   1.8364   1.528  0.141
E_1         1.1558   0.9784   1.181  0.250
E_2         1.3141   0.8228   1.597  0.124
G_0         0.3799   0.6897   0.551  0.587
A*A        -0.0018   0.0021  -0.888  0.384
B*B        -0.0006   0.0036  -0.159  0.875
C*C        -0.0015   0.0004  -3.594  0.002
D*D       -49.3222  77.7789  -0.634  0.533
F*F         0.0599   0.2079   0.288  0.776
A*B         0.0002   0.0020   0.107  0.916
A*C         0.0006   0.0008   0.774  0.447
A*D         0.1928   0.3925   0.491  0.628
A*F        -0.0054   0.0209  -0.258  0.799
B*C         0.0003   0.0010   0.314  0.757
B*D        -0.0635   0.4659  -0.136  0.893
B*F        -0.0319   0.0247  -1.291  0.210
C*D        -0.0128   0.1989  -0.064  0.949
C*F         0.0054   0.0089   0.609  0.549
D*F        -2.9227   2.8855  -1.013  0.322


S = 2.04356    PRESS = 427.256
R-Sq = 73.20%  R-Sq(pred) = 0.00%  R-Sq(adj) = 45.19%


Analysis of Variance for R6

Source          DF   Seq SS   Adj SS  Adj MS     F      P
Regression      23  250.994  250.994  10.913  2.61  0.014
  Linear         8  175.670   46.101   5.763  1.38  0.259
  Square         5   55.248   60.211  12.042  2.88  0.038
  Interaction   10   20.076   20.076   2.008  0.48  0.885
Residual Error  22   91.875   91.875   4.176
  Lack-of-Fit   21   89.875   89.875   4.280  2.14  0.498
  Pure Error     1    2.000    2.000   2.000
Total           45  342.870


Unusual Observations for R6

Obs  StdOrder      R6    Fit  SE Fit  Residual  St Resid
 51        51   1.000  4.318   1.272    -3.318     -2.07 R
 53        53  10.000  6.717   1.621     3.283      2.64 R

R denotes an observation with a large standardized residual.
```

Response Surface Regression: R7 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R7

Term	Coef	SE Coef	T	P
Constant	19.3419	18.6213	1.039	0.310
A	-0.2387	0.2878	-0.829	0.416
B	-0.2691	0.4720	-0.570	0.574
C	0.1326	0.0923	1.437	0.165
D	3.9724	39.6008	0.100	0.921
F	1.7437	1.6021	1.088	0.288
E_1	0.4366	0.8536	0.511	0.614
E_2	1.1701	0.7178	1.630	0.117
G_0	0.4196	0.6018	0.697	0.493
A*A	0.0004	0.0018	0.237	0.814
B*B	0.0022	0.0032	0.710	0.485
C*C	-0.0015	0.0004	-4.219	0.000
D*D	-48.8635	67.8582	-0.720	0.479
F*F	-0.0760	0.1814	-0.419	0.679
A*B	0.0010	0.0017	0.561	0.580
A*C	0.0010	0.0007	1.526	0.141
A*D	0.3679	0.3424	1.074	0.294
A*F	-0.0044	0.0182	-0.240	0.812
B*C	-0.0002	0.0009	-0.266	0.793
B*D	-0.2706	0.4065	-0.666	0.513
B*F	-0.0275	0.0216	-1.275	0.216
C*D	0.0808	0.1736	0.465	0.646
C*F	0.0064	0.0078	0.819	0.422
D*F	1.9321	2.5174	0.767	0.451

S = 1.78290   PRESS = 307.760
R-Sq = 79.09% R-Sq(pred) = 7.96% R-Sq(adj) = 57.22%

Analysis of Variance for R7

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	264.437	264.4372	11.4973	3.62	0.002
Linear	8	171.648	31.5257	3.9407	1.24	0.323
Square	5	56.110	62.0689	12.4138	3.91	0.011
Interaction	10	36.679	36.6790	3.6679	1.15	0.370
Residual Error	22	69.932	69.9324	3.1787		
Lack-of-Fit	21	69.932	69.9324	3.3301	*	*
Pure Error	1	0.000	0.0000	0.0000		
Total	45	334.370				

Unusual Observations for R7

Obs	StdOrder	R7	Fit	SE Fit	Residual	St Resid
7	7	9.000	5.939	1.082	3.061	2.16 R
51	51	1.000	3.954	1.110	-2.954	-2.12 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R8 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R8

Term	Coef	SE Coef	T	P
Constant	4.10844	0.211214	19.452	0.000
A	0.00321	0.003264	0.984	0.336
B	-0.00496	0.005354	-0.926	0.364
C	-0.00214	0.001047	-2.049	0.053
D	0.35292	0.449177	0.786	0.440
F	-0.00343	0.018172	-0.189	0.852
E_1	-0.01897	0.009682	-1.960	0.063
E_2	0.01385	0.008142	1.700	0.103
G_0	-0.00564	0.006825	-0.826	0.417
A*A	-0.00001	0.000020	-0.633	0.533
B*B	0.00004	0.000036	1.187	0.248
C*C	-0.00000	0.000004	-0.382	0.706
D*D	-0.89144	0.769690	-1.158	0.259
F*F	0.00160	0.002057	0.776	0.446
A*B	-0.00002	0.000020	-0.991	0.333
A*C	0.00001	0.000008	0.805	0.430
A*D	-0.00267	0.003884	-0.688	0.498
A*F	-0.00018	0.000207	-0.892	0.382
B*C	0.00001	0.000010	1.198	0.244
B*D	-0.00235	0.004611	-0.509	0.615
B*F	0.00006	0.000245	0.238	0.814
C*D	0.00498	0.001969	2.531	0.019
C*F	0.00014	0.000088	1.548	0.136
D*F	0.00019	0.028554	0.007	0.995

S = 0.0202228 PRESS = 0.0539185
R-Sq = 73.82% R-Sq(pred) = 0.00% R-Sq(adj) = 46.44%

Analysis of Variance for R8

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	0.025365	0.025365	0.001103	2.70	0.012
Linear	8	0.020053	0.009451	0.001181	2.89	0.023
Square	5	0.000568	0.001195	0.000239	0.58	0.712
Interaction	10	0.004745	0.004745	0.000474	1.16	0.366
Residual Error	22	0.008997	0.008997	0.000409		
Lack-of-Fit	21	0.008617	0.008617	0.000410	1.08	0.653
Pure Error	1	0.000380	0.000380	0.000380		
Total	45	0.034362				

Unusual Observations for R8

Obs	StdOrder	R8	Fit	SE Fit	Residual	St Resid
15	15	3.872	3.906	0.017	-0.034	-3.03 R
53	53	4.041	4.002	0.016	0.039	3.15 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R9 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R9

Term	Coef	SE Coef	T	P
Constant	5.36659	1.37433	3.905	0.001
A	-0.02448	0.02124	-1.152	0.262
B	0.03742	0.03483	1.074	0.294
C	-0.00109	0.00681	-0.161	0.874
D	-2.14165	2.92271	-0.733	0.471
F	0.06513	0.11825	0.551	0.587
E_1	-0.04959	0.06300	-0.787	0.440
E_2	0.01157	0.05298	0.218	0.829
G_0	0.05210	0.04441	1.173	0.253
A*A	0.00022	0.00013	1.636	0.116
B*B	-0.00025	0.00023	-1.059	0.301
C*C	0.00001	0.00003	0.236	0.816
D*D	6.15805	5.00824	1.230	0.232
F*F	-0.00198	0.01339	-0.148	0.884
A*B	0.00001	0.00013	0.049	0.961
A*C	-0.00001	0.00005	-0.287	0.777
A*D	-0.00609	0.02527	-0.241	0.812
A*F	-0.00009	0.00135	-0.066	0.948
B*C	0.00003	0.00006	0.484	0.633
B*D	0.00009	0.03000	0.003	0.998
B*F	-0.00072	0.00159	-0.452	0.656
C*D	-0.00233	0.01281	-0.182	0.857
C*F	-0.00005	0.00057	-0.087	0.932
D*F	0.04212	0.18580	0.227	0.823

S = 0.131586   PRESS = 1.40816
R-Sq = 33.43% R-Sq(pred) = 0.00% R-Sq(adj) = 0.00%

Analysis of Variance for R9

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	0.191267	0.191267	0.008316	0.48	0.956
Linear	8	0.080207	0.110836	0.013854	0.80	0.609
Square	5	0.089127	0.074375	0.014875	0.86	0.524
Interaction	10	0.021933	0.021933	0.002193	0.13	0.999
Residual Error	22	0.380928	0.380928	0.017315		
Lack-of-Fit	21	0.377040	0.377040	0.017954	4.62	0.354
Pure Error	1	0.003889	0.003889	0.003889		
Total	45	0.572195				

Unusual Observations for R9

Obs	StdOrder	R9	Fit	SE Fit	Residual	St Resid
5	5	5.257	5.743	0.077	-0.486	-4.56 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R10 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R10

Term	Coef	SE Coef	T	P
Constant	63.189	42.207	1.497	0.149

A	0.322	0.652	0.494	0.626
B	-1.400	1.070	-1.308	0.204
C	-0.238	0.209	-1.139	0.267
D	-154.759	89.758	-1.724	0.099
F	-1.021	3.631	-0.281	0.781
E_1	-5.647	1.935	-2.919	0.008
E_2	-4.319	1.627	-2.655	0.014
G_0	-2.170	1.364	-1.591	0.126
A*A	-0.000	0.004	-0.081	0.936
B*B	0.009	0.007	1.208	0.240
C*C	-0.000	0.001	-0.606	0.551
D*D	296.569	153.806	1.928	0.067
F*F	0.352	0.411	0.857	0.400
A*B	-0.001	0.004	-0.182	0.857
A*C	0.001	0.002	0.953	0.351
A*D	-0.268	0.776	-0.345	0.733
A*F	-0.101	0.041	-2.436	0.023
B*C	0.001	0.002	0.462	0.649
B*D	0.405	0.921	0.440	0.664
B*F	0.071	0.049	1.450	0.161
C*D	0.465	0.393	1.182	0.250
C*F	0.018	0.018	1.015	0.321
D*F	1.491	5.706	0.261	0.796

S = 4.04109   PRESS = 2213.32
R-Sq = 63.78% R-Sq(pred) = 0.00% R-Sq(adj) = 25.91%

Analysis of Variance for R10

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	632.56	632.56	27.50	1.68	0.113
Linear	8	336.59	336.60	42.07	2.58	0.038
Square	5	127.01	118.89	23.78	1.46	0.244
Interaction	10	168.96	168.96	16.90	1.03	0.448
Residual Error	22	359.27	359.27	16.33		
Lack-of-Fit	21	346.77	346.77	16.51	1.32	0.606
Pure Error	1	12.50	12.50	12.50		
Total	45	991.83				

Unusual Observations for R10

Obs	StdOrder	R10	Fit	SE Fit	Residual	St Resid
1	1	0.000	4.045	3.531	-4.045	-2.06 R
51	51	18.000	9.313	2.515	8.687	2.75 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R11 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R11

Term	Coef	SE Coef	T	P
Constant	-16.723	77.992	-0.214	0.832
A	3.444	1.205	2.857	0.009
B	-2.844	1.977	-1.439	0.164
C	-0.390	0.387	-1.010	0.324

D	244.446	165.862	1.474	0.155
F	-4.541	6.710	-0.677	0.506
E_1	4.260	3.575	1.192	0.246
E_2	3.001	3.007	0.998	0.329
G_0	-1.055	2.520	-0.419	0.680
A*A	-0.012	0.008	-1.538	0.138
B*B	0.023	0.013	1.768	0.091
C*C	-0.003	0.002	-1.894	0.071
D*D	-498.278	284.213	-1.753	0.093
F*F	0.506	0.760	0.667	0.512
A*B	-0.022	0.007	-3.076	0.006
A*C	0.010	0.003	3.388	0.003
A*D	-2.339	1.434	-1.631	0.117
A*F	-0.141	0.076	-1.847	0.078
B*C	0.002	0.004	0.489	0.630
B*D	1.862	1.703	1.094	0.286
B*F	0.196	0.090	2.174	0.041
C*D	0.077	0.727	0.105	0.917
C*F	0.008	0.032	0.257	0.799
D*F	-7.632	10.544	-0.724	0.477

S = 7.46741   PRESS = 7024.32
R-Sq = 73.77% R-Sq(pred) = 0.00% R-Sq(adj) = 46.34%

Analysis of Variance for R11

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	3449.47	3449.47	149.98	2.69	0.012
Linear	8	1610.86	754.02	94.25	1.69	0.157
Square	5	490.98	582.56	116.51	2.09	0.105
Interaction	10	1347.64	1347.64	134.76	2.42	0.041
Residual Error	22	1226.77	1226.77	55.76		
Lack-of-Fit	21	1211.65	1211.65	57.70	3.81	0.386
Pure Error	1	15.12	15.12	15.12		
Total	45	4676.24				

Unusual Observations for R11

Obs	StdOrder	R11	Fit	SE Fit	Residual	St Resid
14	14	14.500	7.300	6.781	7.200	2.30 R
79	79	19.000	6.270	4.837	12.730	2.24 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R12 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R12

Term	Coef	SE Coef	T	P
Constant	44.114	89.585	0.492	0.627
A	3.833	1.385	2.768	0.011
B	-5.003	2.271	-2.203	0.038
C	-0.376	0.444	-0.848	0.406
D	359.639	190.515	1.888	0.072
F	-7.392	7.708	-0.959	0.348
E_1	1.272	4.107	0.310	0.760

E_2	4.019	3.453	1.164	0.257
G_0	-2.247	2.895	-0.776	0.446
A*A	-0.018	0.009	-2.137	0.044
B*B	0.035	0.015	2.300	0.031
C*C	-0.001	0.002	-0.478	0.637
D*D	-726.065	326.459	-2.224	0.037
F*F	0.207	0.873	0.237	0.815
A*B	-0.016	0.008	-1.883	0.073
A*C	0.006	0.003	1.923	0.068
A*D	-2.320	1.647	-1.408	0.173
A*F	-0.080	0.088	-0.907	0.374
B*C	0.002	0.004	0.446	0.660
B*D	1.727	1.956	0.883	0.387
B*F	0.150	0.104	1.450	0.161
C*D	0.062	0.835	0.074	0.941
C*F	0.028	0.037	0.741	0.467
D*F	2.089	12.111	0.173	0.865

S = 8.57737   PRESS = 8234.81
R-Sq = 73.08% R-Sq(pred) = 0.00% R-Sq(adj) = 44.94%

Analysis of Variance for R12

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	4394.8	4394.8	191.08	2.60	0.014
Linear	8	2841.2	1334.7	166.84	2.27	0.061
Square	5	987.3	864.3	172.85	2.35	0.075
Interaction	10	566.3	566.3	56.63	0.77	0.656
Residual Error	22	1618.6	1618.6	73.57		
Lack-of-Fit	21	1428.4	1428.4	68.02	0.36	0.891
Pure Error	1	190.1	190.1	190.13		
Total	45	6013.4				

Unusual Observations for R12

Obs	StdOrder	R12	Fit	SE Fit	Residual	St Resid
34	34	0.500	14.170	5.871	-13.670	-2.19 R
47	47	5.000	-6.410	6.639	11.410	2.10 R
79	79	17.500	2.305	5.555	15.195	2.33 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R13 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R13

Term	Coef	SE Coef	T	P
Constant	78.678	85.474	0.920	0.367
A	-0.425	1.321	-0.322	0.751
B	-2.253	2.166	-1.040	0.310
C	0.105	0.424	0.248	0.806
D	214.832	181.774	1.182	0.250
F	-5.439	7.354	-0.740	0.467
E_1	-6.164	3.918	-1.573	0.130
E_2	-0.719	3.295	-0.218	0.829
G_0	-2.461	2.762	-0.891	0.383

A*A	0.002	0.008	0.209	0.837
B*B	0.013	0.015	0.878	0.389
C*C	0.001	0.002	0.352	0.729
D*D	-436.222	311.480	-1.400	0.175
F*F	-0.511	0.833	-0.614	0.545
A*B	0.004	0.008	0.541	0.594
A*C	0.001	0.003	0.186	0.854
A*D	-0.601	1.572	-0.383	0.706
A*F	-0.010	0.084	-0.124	0.902
B*C	-0.002	0.004	-0.534	0.599
B*D	-0.057	1.866	-0.030	0.976
B*F	0.105	0.099	1.058	0.302
C*D	0.055	0.797	0.068	0.946
C*F	-0.004	0.036	-0.121	0.905
D*F	1.103	11.555	0.095	0.925

S = 8.18380   PRESS = 6748.50
R-Sq = 41.53% R-Sq(pred) = 0.00% R-Sq(adj) = 0.00%

Analysis of Variance for R13

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	1046.7	1046.7	45.51	0.68	0.818
Linear	8	550.4	487.7	60.97	0.91	0.526
Square	5	326.3	258.4	51.67	0.77	0.580
Interaction	10	170.0	170.0	17.00	0.25	0.985
Residual Error	22	1473.4	1473.4	66.97		
Lack-of-Fit	21	1108.9	1108.9	52.81	0.14	0.984
Pure Error	1	364.5	364.5	364.50		
Total	45	2520.1				

Unusual Observations for R13

Obs	StdOrder	R13	Fit	SE Fit	Residual	St Resid
46	46	-29.500	-14.027	4.648	-15.473	-2.30 R
55	55	-31.000	-16.567	5.521	-14.433	-2.39 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R14 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R14

Term	Coef	SE Coef	T	P
Constant	-100.531	83.693	-1.201	0.242
A	1.246	1.294	0.963	0.346
B	1.906	2.121	0.898	0.379
C	0.010	0.415	0.024	0.981
D	-20.440	177.985	-0.115	0.910
F	-3.597	7.201	-0.500	0.622
E_1	12.133	3.837	3.162	0.005
E_2	-3.293	3.226	-1.021	0.319
G_0	-0.136	2.705	-0.050	0.960
A*A	-0.006	0.008	-0.747	0.463
B*B	-0.009	0.014	-0.653	0.520
C*C	-0.000	0.002	-0.035	0.972

D*D	166.986	304.987	0.548	0.590
F*F	-0.271	0.815	-0.333	0.742
A*B	-0.009	0.008	-1.202	0.242
A*C	0.006	0.003	2.010	0.057
A*D	-0.460	1.539	-0.299	0.768
A*F	-0.016	0.082	-0.199	0.844
B*C	-0.002	0.004	-0.482	0.635
B*D	0.210	1.827	0.115	0.910
B*F	0.084	0.097	0.869	0.394
C*D	-0.720	0.780	-0.923	0.366
C*F	-0.032	0.035	-0.921	0.367
D*F	3.791	11.315	0.335	0.741

S = 8.01322   PRESS = 6354.17
R-Sq = 64.15% R-Sq(pred) = 0.00% R-Sq(adj) = 26.67%

Analysis of Variance for R14

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	2527.75	2527.75	109.90	1.71	0.106
Linear	8	1732.29	1632.36	204.05	3.18	0.015
Square	5	61.83	92.94	18.59	0.29	0.914
Interaction	10	733.63	733.63	73.36	1.14	0.377
Residual Error	22	1412.66	1412.66	64.21		
Lack-of-Fit	21	1367.53	1367.53	65.12	1.44	0.585
Pure Error	1	45.13	45.13	45.13		
Total	45	3940.41				

Response Surface Regression: R15 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R15

Term	Coef	SE Coef	T	P
Constant	25.2524	12.1173	2.084	0.049
A	-0.0850	0.1873	-0.454	0.654
B	-0.3568	0.3071	-1.162	0.258
C	0.0059	0.0601	0.098	0.923
D	-13.7048	25.7691	-0.532	0.600
F	1.2770	1.0425	1.225	0.234
E_1	-1.3743	0.5555	-2.474	0.022
E_2	-0.0700	0.4671	-0.150	0.882
G_0	0.3417	0.3916	0.873	0.392
A*A	0.0004	0.0012	0.306	0.763
B*B	0.0013	0.0021	0.632	0.534
C*C	-0.0003	0.0002	-1.219	0.236
D*D	-43.5610	44.1568	-0.987	0.335
F*F	0.0867	0.1180	0.734	0.470
A*B	0.0008	0.0011	0.694	0.495
A*C	-0.0004	0.0004	-0.971	0.342
A*D	0.1161	0.2228	0.521	0.607
A*F	-0.0033	0.0119	-0.274	0.787
B*C	0.0010	0.0006	1.767	0.091
B*D	0.3742	0.2645	1.415	0.171
B*F	-0.0209	0.0140	-1.493	0.150
C*D	-0.0649	0.1129	-0.574	0.572

C*F	0.0037	0.0050	0.736	0.470
D*F	-0.6847	1.6382	-0.418	0.680

S = 1.16017   PRESS = 136.819
R-Sq = 65.46% R-Sq(pred) = 0.00% R-Sq(adj) = 29.36%

Analysis of Variance for R15

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	23	56.127	56.127	2.4403	1.81	0.084
Linear	8	29.876	18.497	2.3121	1.72	0.150
Square	5	6.627	4.440	0.8880	0.66	0.658
Interaction	10	19.625	19.625	1.9625	1.46	0.221
Residual Error	22	29.612	29.612	1.3460		
Lack-of-Fit	21	21.612	21.612	1.0291	0.13	0.989
Pure Error	1	8.000	8.000	8.0000		
Total	45	85.739				

Unusual Observations for R15

Obs	StdOrder	R15	Fit	SE Fit	Residual	St Resid
46	46	4.000	6.671	0.659	-2.671	-2.80 R

R denotes an observation with a large standardized residual.

Response Surface Regression: R16 versus A, B, C, D, F, E_1, E_2, G_0

The analysis was done using uncoded units.

Estimated Regression Coefficients for R16

Term	Coef	SE Coef	T	P
Constant	17.4358	14.0226	1.243	0.227
A	-0.0572	0.2167	-0.264	0.794
B	-0.0850	0.3554	-0.239	0.813
C	-0.0614	0.0695	-0.883	0.387
D	-34.7939	29.8211	-1.167	0.256
F	1.0203	1.2065	0.846	0.407
E_1	-0.8060	0.6428	-1.254	0.223
E_2	0.2651	0.5406	0.490	0.629
G_0	-1.2396	0.4531	-2.735	0.012
A*A	0.0005	0.0014	0.364	0.719
B*B	-0.0014	0.0024	-0.570	0.574
C*C	-0.0007	0.0003	-2.687	0.013
D*D	38.8475	51.1001	0.760	0.455
F*F	-0.0735	0.1366	-0.538	0.596
A*B	0.0011	0.0013	0.867	0.395
A*C	-0.0002	0.0005	-0.467	0.645
A*D	-0.1942	0.2579	-0.753	0.459
A*F	-0.0121	0.0137	-0.878	0.389
B*C	0.0019	0.0007	2.871	0.009
B*D	0.5197	0.3061	1.698	0.104
B*F	-0.0002	0.0162	-0.015	0.988
C*D	0.0331	0.1307	0.253	0.803
C*F	0.0112	0.0058	1.913	0.069
D*F	-2.1145	1.8957	-1.115	0.277

```
S = 1.34260    PRESS = 234.355
R-Sq = 74.57%  R-Sq(pred) = 0.00%  R-Sq(adj) = 47.98%


Analysis of Variance for R16

Source          DF   Seq SS    Adj SS  Adj MS     F      P
Regression      23  116.278  116.2779  5.0556  2.80  0.009
  Linear         8   71.430   28.7891  3.5986  2.00  0.095
  Square         5    8.228   14.5341  2.9068  1.61  0.198
  Interaction   10   36.619   36.6191  3.6619  2.03  0.080
Residual Error  22   39.657   39.6568  1.8026
  Lack-of-Fit   21   39.157   39.1568  1.8646  3.73  0.390
  Pure Error     1    0.500    0.5000  0.5000
Total           45  155.935


Unusual Observations for R16

Obs  StdOrder    R16    Fit  SE Fit  Residual  St Resid
  3         3  5.000  7.615   0.907    -2.615     -2.64 R
  6         6  3.000  5.075   0.882    -2.075     -2.05 R
 13        13  9.000  7.282   1.108     1.718      2.27 R
 33        33  9.000  7.247   1.018     1.753      2.00 R

R denotes an observation with a large standardized residual.
```

2nd Regression analysis

_R1 versus A, B, C, D, E_2, G_0, C*C, A*B, B*C, C*D

```
The regression equation is
R1 = 7.89 + 0.0726 A - 0.0424 B - 0.0456 C + 2.93 D - 0.253 E_2 - 0.718 G_0
     - 0.000849 C*C - 0.00096 A*B + 0.00193 B*C + 0.0828 C*D


52 cases used, 37 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant        7.893      4.951   1.59  0.119
A             0.07259    0.07665   0.95  0.349
B            -0.04243    0.06759  -0.63  0.534
C            -0.04558    0.04550  -1.00  0.322
D               2.929      3.789   0.77  0.444
E_2           -0.2533     0.4248  -0.60  0.554
G_0           -0.7183     0.3863  -1.86  0.070
C*C        -0.0008494  0.0002259  -3.76  0.001
A*B         -0.000961   0.001027  -0.94  0.355
B*C         0.0019292  0.0005436   3.55  0.001
C*D           0.08283    0.09380   0.88  0.382


S = 1.34497   R-Sq = 67.3%   R-Sq(adj) = 59.3%


Analysis of Variance

Source          DF       SS      MS     F      P
```

```
Regression      10  152.660  15.266  8.44  0.000
Residual Error  41   74.167   1.809
Total           51  226.827


Source  DF  Seq SS
A        1   5.530
B        1  12.636
C        1  74.961
D        1  11.694
E_2      1   1.103
G_0      1   7.514
C*C      1  14.751
A*B      1   0.015
B*C      1  23.046
C*D      1   1.411


Unusual Observations

Obs     A     R1    Fit  SE Fit  Residual  St Resid
 14  40.0  9.000  5.839   0.764     3.161     2.85R
 20  40.0      *  5.588   1.488         *        * X
 25  60.0      *  6.560   1.095         *        * X
 32  80.0      *  7.034   1.223         *        * X
 35  60.0      *  8.417   1.264         *        * X
 38  40.0      *  6.456   1.164         *        * X
 40  40.0      *  8.949   1.219         *        * X
 48  60.0      *  5.886   1.339         *        * X
 51  80.0  9.000  6.407   0.405     2.593     2.02R
 62  40.0      *  6.297   1.175         *        * X
 72  40.0      *  6.297   1.175         *        * X
 76  80.0      *  5.931   1.350         *        * X
 78  40.0      *  4.869   1.476         *        * X
 81  80.0  5.000  7.908   0.582    -2.908    -2.40R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

Regression analysis: R2 versus B, C, E_1, G_0, C*C, B*C

```
The regression equation is
R2 = 11.3 - 0.0626 B + 0.0141 C - 0.927 E_1 - 1.15 G_0 - 0.000624 C*C
     + 0.00112 B*C


53 cases used, 36 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant       11.255      1.914   5.88  0.000
B            -0.06262    0.02580  -2.43  0.019
C             0.01415    0.04228   0.33  0.739
E_1           -0.9271     0.4257  -2.18  0.035
G_0           -1.1544     0.3989  -2.89  0.006
C*C        -0.0006244  0.0002379  -2.63  0.012
B*C         0.0011170  0.0005513   2.03  0.049


S = 1.42196   R-Sq = 60.1%   R-Sq(adj) = 54.9%
```

```
Analysis of Variance

Source          DF       SS      MS      F      P
Regression       6  140.310  23.385  11.57  0.000
Residual Error  46   93.010   2.022
Total           52  233.321


Source  DF  Seq SS
B        1  10.471
C        1  81.643
E_1      1  11.055
G_0      1  19.633
C*C      1   9.206
B*C      1   8.302


Unusual Observations

Obs     B     R2    Fit  SE Fit  Residual  St Resid
 20  60.0      *  8.443   0.941         *         * X
 22  60.0      *  8.216   0.936         *         * X
 36  60.0      *  8.216   0.936         *         * X
 38  60.0      *  9.370   0.959         *         * X
 41  60.0  9.000  7.289   0.945     1.711      1.61 X
 42  60.0      *  8.443   0.941         *         * X
 46  75.0  1.000  5.393   0.434    -4.393     -3.24R
 48  60.0      *  9.370   0.959         *         * X
 76  60.0      *  9.370   0.959         *         * X
 78  60.0      *  8.216   0.936         *         * X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

Regression analysis: R3 versus D, C, G_0, C*C, C*D

```
The regression equation is
R3 = 4.04 + 15.1 D + 0.105 C - 0.250 G_0 - 0.000459 C*C - 0.185 C*D


53 cases used, 36 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant       4.0447     0.8219   4.92  0.000
D              15.105      3.512   4.30  0.000
C             0.10483    0.02601   4.03  0.000
G_0           -0.2505     0.3625  -0.69  0.493
C*C        -0.0004590  0.0002004  -2.29  0.027
C*D          -0.18528    0.08626  -2.15  0.037


S = 1.29022   R-Sq = 50.6%   R-Sq(adj) = 45.4%


Analysis of Variance

Source          DF      SS      MS     F      P
Regression       5  80.213  16.043  9.64  0.000
Residual Error  47  78.240   1.665
```

```
Total           52  158.453


Source  DF  Seq SS
D        1  43.087
C        1  16.276
G_0      1   1.136
C*C      1  12.034
C*D      1   7.680


Unusual Observations

Obs      D     R3    Fit  SE Fit  Residual  St Resid
 20  0.100      *  9.596   1.026         *         * X
 21  0.200  3.000  7.697   0.310    -4.697     -3.75R
 25  0.100      *  9.345   1.020         *         * X
 32  0.100      *  9.596   1.026         *         * X
 35  0.100      *  9.596   1.026         *         * X
 40  0.100      *  9.596   1.026         *         * X
 48  0.100      *  9.596   1.026         *         * X
 62  0.100      *  9.345   1.020         *         * X
 72  0.100      *  9.345   1.020         *         * X
 76  0.100      *  9.596   1.026         *         * X
 78  0.100      *  9.345   1.020         *         * X
 86  0.200  6.000  9.003   0.547    -3.003     -2.57R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

Regression analysis: R4 versus D, A, F, B, E_1, A*B, A*F, B*D

```
The regression equation is
R4 = 0.0152 + 0.081 D - 0.000057 A - 0.00279 F + 0.000372 B + 0.00933 E_1
     - 0.000002 A*B + 0.000033 A*F - 0.00141 B*D


53 cases used, 36 cases contain missing values


Predictor          Coef     SE Coef      T      P
Constant        0.01523     0.04762   0.32  0.751
D                0.0809      0.1208   0.67  0.507
A            -0.0000574   0.0005890  -0.10  0.923
F             -0.002791    0.003949  -0.71  0.483
B             0.0003718   0.0006387   0.58  0.563
E_1            0.009335    0.003169   2.95  0.005
A*B         -0.00000196  0.00000767  -0.26  0.800
A*F          0.00003276  0.00005826   0.56  0.577
B*D           -0.001408    0.001642  -0.86  0.396


S = 0.0106440   R-Sq = 24.1%   R-Sq(adj) = 10.3%


Analysis of Variance

Source          DF         SS         MS     F      P
Regression       8  0.0015800  0.0001975  1.74  0.115
Residual Error  44  0.0049850  0.0001133
Total           52  0.0065650
```

Source	DF	Seq SS
D	1	0.0002645
A	1	0.0001839
F	1	0.0000980
B	1	0.0000001
E_1	1	0.0009229
A*B	1	0.0000064
A*F	1	0.0000208
B*D	1	0.0000833

Unusual Observations

Obs	D	R4	Fit	SE Fit	Residual	St Resid
46	0.100	0.07250	0.03771	0.00372	0.03479	3.49R
70	0.100	0.01200	0.03362	0.00412	-0.02162	-2.20R

R denotes an observation with a large standardized residual.

Regression analysis: R5 versus C, E_1, E_2, C*C

The regression equation is
R5 = 2.05 + 0.182 C + 0.902 E_1 + 1.09 E_2 - 0.00119 C*C

53 cases used, 36 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	2.0515	0.5054	4.06	0.000
C	0.18234	0.02281	7.99	0.000
E_1	0.9022	0.4705	1.92	0.061
E_2	1.0945	0.4846	2.26	0.029
C*C	-0.0011885	0.0002208	-5.38	0.000

S = 1.40869   R-Sq = 76.2%   R-Sq(adj) = 74.3%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	4	305.504	76.376	38.49	0.000
Residual Error	48	95.251	1.984		
Total	52	400.755			

Source	DF	Seq SS
C	1	236.345
E_1	1	0.095
E_2	1	11.571
C*C	1	57.492

Unusual Observations

Obs	C	R5	Fit	SE Fit	Residual	St Resid
27	55	6.000	9.579	0.423	-3.579	-2.66R
51	10	1.000	3.756	0.386	-2.756	-2.03R

```
 53  10  9.000  4.851   0.416     4.149      3.08R

R denotes an observation with a large standardized residual.
```

Regression analysis: R6 versus B, C, F, E_1, E_2, C*C, B*F

```
The regression equation is
R6 = - 1.12 + 0.0408 B + 0.201 C + 1.72 F + 0.100 E_1 + 1.25 E_2 - 0.00134 C*C
     - 0.0237 B*F


53 cases used, 36 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant       -1.117      2.839  -0.39  0.696
B             0.04080    0.03533   1.15  0.254
C             0.20087    0.03099   6.48  0.000
F               1.720      1.046   1.64  0.107
E_1            0.0997     0.6201   0.16  0.873
E_2            1.2531     0.6258   2.00  0.051
C*C        -0.0013371  0.0002992  -4.47  0.000
B*F          -0.02375    0.01413  -1.68  0.100


S = 1.81427   R-Sq = 70.7%   R-Sq(adj) = 66.1%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       7  356.747  50.964  15.48  0.000
Residual Error  45  148.120   3.292
Total           52  504.868


Source  DF   Seq SS
B        1    3.962
C        1  255.739
F        1    0.508
E_1      1   14.484
E_2      1   14.760
C*C      1   57.992
B*F      1    9.301


Unusual Observations

Obs     B      R6    Fit  SE Fit  Residual  St Resid
 26  75.0   8.000  3.917   0.552     4.083     2.36R
 53  90.0  10.000  5.682   0.816     4.318     2.66R
 55  60.0   8.000  4.487   0.780     3.513     2.14R

R denotes an observation with a large standardized residual.
```

Regression analysis: R7 versus F, B, A, C, E_2, C*C, A*C, B*F

```
The regression equation is
R7 = 2.34 + 0.668 F + 0.0391 B - 0.0407 A + 0.138 C + 1.23 E_2 - 0.00135 C*C
     + 0.000865 A*C - 0.0116 B*F
```

53 cases used, 36 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	2.336	2.624	0.89	0.378
F	0.6678	0.8951	0.75	0.460
B	0.03907	0.03094	1.26	0.213
A	-0.04066	0.02243	-1.81	0.077
C	0.13831	0.03571	3.87	0.000
E_2	1.2260	0.4876	2.51	0.016
C*C	-0.0013521	0.0002611	-5.18	0.000
A*C	0.0008655	0.0004120	2.10	0.041
B*F	-0.01159	0.01212	-0.96	0.344

S = 1.57844   R-Sq = 74.4%   R-Sq(adj) = 69.8%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	8	318.677	39.835	15.99	0.000
Residual Error	44	109.625	2.491		
Total	52	428.302			

Source	DF	Seq SS
F	1	8.552
B	1	0.532
A	1	10.155
C	1	200.348
E_2	1	27.907
C*C	1	57.774
A*C	1	11.129
B*F	1	2.279

Unusual Observations

Obs	F	R7	Fit	SE Fit	Residual	St Resid
7	2.00	9.000	6.056	0.607	2.944	2.02R
14	0.00	3.000	5.820	0.828	-2.820	-2.10R
38	0.00	*	8.051	1.217	*	* X
53	0.00	9.000	5.765	0.779	3.235	2.36R
78	0.00	*	6.825	1.177	*	* X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Regression analysis: R8 versus B, D, F, C, E_1, E_2, B*B, B*C, C*D, C*F

The regression equation is
R8 = 4.15 - 0.00243 B - 0.282 D - 0.00321 F - 0.00116 C - 0.0216 E_1
     + 0.0124 E_2 + 0.000015 B*B + 0.000009 B*C + 0.00293 C*D + 0.000088 C*F

53 cases used, 36 cases contain missing values

Predictor	Coef	SE Coef	T	P

Constant	4.1469	0.1550	26.76	0.000
B	-0.002428	0.004129	-0.59	0.560
D	-0.28181	0.05692	-4.95	0.000
F	-0.003213	0.002779	-1.16	0.254
C	-0.0011625	0.0006822	-1.70	0.096
E_1	-0.021560	0.007120	-3.03	0.004
E_2	0.012417	0.007352	1.69	0.099
B*B	0.00001537	0.00002763	0.56	0.581
B*C	0.00000857	0.00000784	1.09	0.281
C*D	0.002930	0.001401	2.09	0.043
C*F	0.00008759	0.00005435	1.61	0.115

S = 0.0207758   R-Sq = 60.5%   R-Sq(adj) = 51.1%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	10	0.0277289	0.0027729	6.42	0.000
Residual Error	42	0.0181287	0.0004316		
Total	52	0.0458576			

Source	DF	Seq SS
B	1	0.0002342
D	1	0.0074083
F	1	0.0000898
C	1	0.0057180
E_1	1	0.0099434
E_2	1	0.0010968
B*B	1	0.0000175
B*C	1	0.0006001
C*D	1	0.0014998
C*F	1	0.0011211

Unusual Observations

Obs	B	R8	Fit	SE Fit	Residual	St Resid
15	90.0	3.87224	3.94702	0.00895	-0.07477	-3.99R
20	60.0	*	3.98239	0.01742	*	* X
25	75.0	*	4.02261	0.01667	*	* X
32	75.0	*	4.02393	0.01645	*	* X
35	90.0	*	4.02733	0.02086	*	* X
40	90.0	*	4.03710	0.01866	*	* X
48	60.0	*	4.00395	0.01802	*	* X
62	75.0	*	4.01284	0.01888	*	* X
72	75.0	*	4.01284	0.01888	*	* X
76	60.0	*	4.02746	0.01908	*	* X
78	60.0	*	3.99285	0.01997	*	* X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Regression analysis: R9 versus A, D, G_0, A*A, D*D

The regression equation is
R9 = 6.71 - 0.0241 A - 1.07 D + 0.0448 G_0 + 0.000200 A*A + 2.62 D*D

53 cases used, 36 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	6.7116	0.3235	20.75	0.000
A	-0.024122	0.009712	-2.48	0.017
D	-1.073	1.215	-0.88	0.382
G_0	0.04479	0.02870	1.56	0.125
A*A	0.00020041	0.00007872	2.55	0.014
D*D	2.618	2.935	0.89	0.377

S = 0.101680   R-Sq = 16.1%   R-Sq(adj) = 7.2%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	5	0.09316	0.01863	1.80	0.131
Residual Error	47	0.48593	0.01034		
Total	52	0.57909			

Source	DF	Seq SS
A	1	0.00360
D	1	0.00018
G_0	1	0.02017
A*A	1	0.06099
D*D	1	0.00823

Unusual Observations

Obs	A	R9	Fit	SE Fit	Residual	St Resid
5	60.0	5.2569	5.8758	0.0357	-0.6189	-6.50R

R denotes an observation with a large standardized residual.

Regression analysis: R10 versus F, A, ...

The regression equation is
R10 = 14.7 + 0.59 F + 0.0942 A - 0.0123 C - 0.0092 B - 116 D - 5.03 E_1
      - 5.25 E_2 - 1.64 G_0 + 256 D*D - 0.0274 A*F + 0.0184 B*F + 0.083 C*D

77 cases used, 12 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	14.729	6.493	2.27	0.027
F	0.586	1.974	0.30	0.767
A	0.09417	0.04730	1.99	0.051
C	-0.01228	0.03562	-0.34	0.731
B	-0.00919	0.06478	-0.14	0.888
D	-115.78	40.21	-2.88	0.005
E_1	-5.026	1.191	-4.22	0.000
E_2	-5.250	1.086	-4.83	0.000
G_0	-1.6351	0.9436	-1.73	0.088
D*D	255.63	97.79	2.61	0.011
A*F	-0.02738	0.01896	-1.44	0.154
B*F	0.01836	0.02531	0.73	0.471

```
C*D          0.0834   0.1638   0.51  0.613


S = 4.01368   R-Sq = 40.8%   R-Sq(adj) = 29.7%


Analysis of Variance

Source          DF       SS     MS     F      P
Regression      12   711.66  59.30  3.68  0.000
Residual Error  64  1031.02  16.11
Total           76  1742.68


Source  DF  Seq SS
F        1   10.56
A        1   41.11
C        1    1.26
B        1    9.69
D        1   17.70
E_1      1   86.03
E_2      1  361.70
G_0      1   36.52
D*D      1  101.78
A*F      1   32.35
B*F      1    8.78
C*D      1    4.17


Unusual Observations

Obs     F     R10     Fit  SE Fit  Residual  St Resid
 51  0.00  18.000   8.686   1.585     9.314     2.53R
 52  0.00  19.000  10.684   1.762     8.316     2.31R
 58  0.00  20.000  10.739   1.854     9.261     2.60R
 61  2.00   1.000   9.106   1.461    -8.106    -2.17R
 81  4.00   9.000   1.789   1.966     7.211     2.06R
 82  2.00   4.000  12.294   1.392    -8.294    -2.20R

R denotes an observation with a large standardized residual.
```

Regression analysis: R11 versus C, F, ...

```
The regression equation is
R11 = - 33.9 - 0.263 C - 4.01 F + 1.92 A - 0.85 B + 136 D - 0.11 E_1
      - 0.00269 A*A + 0.0104 B*B - 0.0168 A*B + 0.00652 A*C - 2.00 A*D
      - 0.0999 A*F + 0.156 B*F


52 cases used, 37 cases contain missing values


Predictor       Coef   SE Coef      T      P
Constant      -33.86     73.87  -0.46  0.649
C            -0.2629    0.1644  -1.60  0.118
F             -4.010     5.254  -0.76  0.450
A             1.9244    0.9688   1.99  0.054
B             -0.855     1.776  -0.48  0.633
D             135.81     77.85   1.74  0.089
E_1           -0.112     2.657  -0.04  0.966
A*A        -0.002690  0.006785  -0.40  0.694
```

```
B*B         0.01041   0.01176   0.89  0.381
A*B       -0.016751  0.006589  -2.54  0.015
A*C        0.006517  0.002403   2.71  0.010
A*D          -2.003     1.160  -1.73  0.093
A*F        -0.09995   0.05074  -1.97  0.056
B*F         0.15581   0.07193   2.17  0.037


S = 8.44171   R-Sq = 53.3%   R-Sq(adj) = 37.3%


Analysis of Variance

Source          DF       SS      MS     F      P
Regression      13  3086.39  237.41  3.33  0.002
Residual Error  38  2707.97   71.26
Total           51  5794.36


Source  DF   Seq SS
C        1  1743.85
F        1    58.65
A        1     0.48
B        1   118.41
D        1    11.33
E_1      1    14.77
A*A      1    17.22
B*B      1    42.28
A*B      1   183.01
A*C      1   343.97
A*D      1    89.82
A*F      1   128.20
B*F      1   334.39


Unusual Observations

Obs    C      R11     Fit  SE Fit  Residual  St Resid
 14   10    14.50    2.61    6.62     11.89     2.27R
 20  100        *   -7.28    7.95         *        * X
 21   10   -23.00    1.21    3.47    -24.21    -3.15R
 40  100        *   15.32    8.15         *        * X
 55   10    12.50   -2.09    4.39     14.59     2.02R
 62  100        *  -11.64    8.38         *        * X
 72  100        *  -11.64    8.38         *        * X
 78  100        *   -9.85    8.89         *        * X
 79   10    19.00    1.29    4.52     17.71     2.48R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

Regression analysis: R12 versus F, A, ...

```
The regression equation is
R12 = 11.8 - 8.59 F + 1.39 A + 0.039 C - 2.16 B + 298 D - 0.00381 A*A
      + 0.0145 B*B - 242 D*D - 0.00612 A*B + 0.00218 A*C - 2.44 A*D + 0.124 B*F


53 cases used, 36 cases contain missing values
```

Predictor	Coef	SE Coef	T	P
Constant	11.82	87.65	0.13	0.893
F	-8.591	5.863	-1.47	0.151
A	1.390	1.134	1.23	0.227
C	0.0389	0.1927	0.20	0.841
B	-2.162	2.086	-1.04	0.306
D	297.7	150.7	1.98	0.055
A*A	-0.003811	0.008214	-0.46	0.645
B*B	0.01450	0.01382	1.05	0.300
D*D	-241.7	311.7	-0.78	0.443
A*B	-0.006116	0.007711	-0.79	0.432
A*C	0.002184	0.002781	0.79	0.437
A*D	-2.439	1.346	-1.81	0.078
B*F	0.12442	0.07941	1.57	0.125

S = 10.1906   R-Sq = 50.2%   R-Sq(adj) = 35.2%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	12	4184.8	348.7	3.36	0.002
Residual Error	40	4154.0	103.8		
Total	52	8338.8			

Source	DF	Seq SS
F	1	21.0
A	1	204.6
C	1	2361.8
B	1	241.0
D	1	502.1
A*A	1	26.2
B*B	1	201.8
D*D	1	82.6
A*B	1	28.2
A*C	1	22.0
A*D	1	238.6
B*F	1	254.9

Unusual Observations

Obs	F	R12	Fit	SE Fit	Residual	St Resid
20	2.00	*	-2.88	9.74	*	* X
21	2.00	-39.00	-1.09	4.54	-37.91	-4.16R
40	4.00	*	2.87	9.21	*	* X
62	0.00	*	-7.36	8.82	*	* X
72	0.00	*	-7.36	8.82	*	* X
78	0.00	*	-0.62	9.66	*	* X
79	4.00	17.50	-3.73	5.39	21.23	2.45R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Regression analysis: R13 versus D, E_1, D*D

The regression equation is
R13 = - 24.4 + 239 D - 3.98 E_1 - 552 D*D

48 cases used, 41 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	-24.387	7.539	-3.23	0.002
D	238.57	80.20	2.97	0.005
E_1	-3.978	2.145	-1.85	0.070
D*D	-552.1	195.0	-2.83	0.007

S = 6.63064   R-Sq = 23.8%   R-Sq(adj) = 18.6%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	604.27	201.42	4.58	0.007
Residual Error	44	1934.47	43.97		
Total	47	2538.74			

Source	DF	Seq SS
D	1	99.47
E_1	1	152.27
D*D	1	352.54

Unusual Observations

Obs	D	R13	Fit	SE Fit	Residual	St Resid
5	0.200	10.000	-2.735	2.110	12.735	2.03R
46	0.100	-29.500	-10.029	2.287	-19.471	-3.13R
55	0.100	-31.000	-10.029	2.287	-20.971	-3.37R

R denotes an observation with a large standardized residual.

Regression analysis: R14 versus A, B, C, E_1, A*B, A*C

The regression equation is
R14 = - 28.1 + 0.446 A + 0.638 B - 0.353 C + 11.4 E_1 - 0.0103 A*B + 0.00629 A*C

52 cases used, 37 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	-28.08	25.97	-1.08	0.285
A	0.4460	0.3897	1.14	0.259
B	0.6379	0.3662	1.74	0.088
C	-0.3526	0.1349	-2.61	0.012
E_1	11.381	2.155	5.28	0.000
A*B	-0.010303	0.005386	-1.91	0.062
A*C	0.006294	0.001954	3.22	0.002

```
S = 7.15108   R-Sq = 46.7%   R-Sq(adj) = 39.6%


Analysis of Variance

Source          DF       SS      MS     F      P
Regression       6  2019.04  336.51  6.58  0.000
Residual Error  45  2301.21   51.14
Total           51  4320.25


Source  DF   Seq SS
A        1     1.12
B        1     0.65
C        1   288.87
E_1      1  1134.11
A*B      1    63.86
A*C      1   530.45


Unusual Observations

Obs     A     R14     Fit  SE Fit  Residual  St Resid
 13  40.0   8.000  11.378   4.670    -3.378     -0.62 X
 20  40.0       *   4.607   5.440         *         * X
 30  40.0       *  -3.388   4.577         *         * X
 38  40.0       *  -6.774   5.552         *         * X
 40  40.0       *  -0.003   4.827         *         * X
 59  40.0       *  -3.388   4.577         *         * X
 62  40.0       *  -3.388   4.577         *         * X
 72  40.0       *  -3.388   4.577         *         * X
 78  40.0       *  -6.774   5.552         *         * X
 86  80.0  -7.000   8.718   2.545   -15.718     -2.35R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

Regression analysis: R15 versus B, F, C, D, E_1, C*C, B*C, D*D, B*F

```
The regression equation is
R15 = 8.22 - 0.0279 B + 0.865 F - 0.0193 C + 15.8 D - 0.621 E_1 - 0.000278 C*C
      + 0.000827 B*C - 33.1 D*D - 0.0114 B*F


53 cases used, 36 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant        8.219      2.701   3.04  0.004
B            -0.02794    0.03044  -0.92  0.364
F              0.8648     0.7106   1.22  0.230
C            -0.01926    0.03774  -0.51  0.613
D               15.79      15.11   1.05  0.302
E_1           -0.6214     0.3717  -1.67  0.102
C*C        -0.0002777  0.0002073  -1.34  0.187
B*C         0.0008265  0.0004801   1.72  0.092
D*D            -33.15      36.32  -0.91  0.366
B*F         -0.011405   0.009568  -1.19  0.240
```

```
S = 1.21806   R-Sq = 40.4%   R-Sq(adj) = 27.9%


Analysis of Variance

Source          DF       SS     MS     F      P
Regression       9   43.221  4.802  3.24  0.004
Residual Error  43   63.797  1.484
Total           52  107.019


Source  DF  Seq SS
B        1   4.767
F        1   0.545
C        1  18.112
D        1   2.255
E_1      1   7.776
C*C      1   0.610
B*C      1   5.741
D*D      1   1.307
B*F      1   2.108


Unusual Observations

Obs     B     R15    Fit  SE Fit  Residual  St Resid
  7  75.0   6.000  8.374   0.378    -2.374     -2.05R
 46  75.0   4.000  7.149   0.437    -3.149     -2.77R
 60  90.0   9.000  6.713   0.624     2.287      2.19R
 64  75.0  10.000  7.674   0.410     2.326      2.03R
 76  60.0       *  8.768   0.974         *         * X
 78  60.0       *  8.046   0.918         *         * X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

Regression analysis: R16 versus D, F, C, B, E_1, G_0, C*C, B*C, B*D, C*F

```
The regression equation is
R16 = 17.5 - 26.9 D - 0.178 F - 0.0244 C - 0.149 B - 0.795 E_1 - 1.39 G_0
      - 0.000601 C*C + 0.00123 B*C + 0.433 B*D + 0.00526 C*F


53 cases used, 36 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant       17.488      3.586   4.88  0.000
D              -26.93      14.97  -1.80  0.079
F             -0.1784     0.1710  -1.04  0.303
C            -0.02442    0.04006  -0.61  0.545
B            -0.14878    0.04680  -3.18  0.003
E_1           -0.7952     0.4045  -1.97  0.056
G_0           -1.3926     0.3799  -3.67  0.001
C*C        -0.0006007  0.0002170  -2.77  0.008
B*C         0.0012345  0.0005144   2.40  0.021
B*D            0.4334     0.2030   2.14  0.039
C*F          0.005263   0.003279   1.61  0.116


S = 1.29585   R-Sq = 61.6%   R-Sq(adj) = 52.4%
```

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	10	113.020	11.302	6.73	0.000
Residual Error	42	70.527	1.679		
Total	52	183.547			

Source	DF	Seq SS
D	1	24.897
F	1	0.117
C	1	22.171
B	1	5.683
E_1	1	5.240
G_0	1	23.567
C*C	1	7.404
B*C	1	12.275
B*D	1	7.339
C*F	1	4.327

Unusual Observations

Obs	D	R16	Fit	SE Fit	Residual	St Resid
3	0.200	5.000	8.292	0.522	-3.292	-2.77R
6	0.200	3.000	6.169	0.439	-3.169	-2.60R
35	0.100	*	7.966	1.034	*	* X
41	0.200	3.000	5.145	0.938	-2.145	-2.40R
48	0.100	*	8.122	1.057	*	* X
76	0.100	*	8.818	1.160	*	* X
78	0.100	*	6.034	1.068	*	* X
81	0.200	5.000	7.513	0.538	-2.513	-2.13R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

3 Regression Analysis

Regression analysis: R1 versus B, C, G_0, C*C, B*C

The regression equation is
R1 = 12.8 - 0.101 B - 0.0209 C - 0.896 G_0 - 0.000817 C*C + 0.00185 B*C

52 cases used, 37 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	12.830	1.872	6.85	0.000
B	-0.10056	0.02514	-4.00	0.000
C	-0.02094	0.04065	-0.52	0.609
G_0	-0.8964	0.3794	-2.36	0.022
C*C	-0.0008168	0.0002236	-3.65	0.001
B*C	0.0018476	0.0005322	3.47	0.001

S = 1.36142   R-Sq = 62.4%   R-Sq(adj) = 58.3%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	5	141.568	28.314	15.28	0.000
Residual Error	46	85.259	1.853		
Total	51	226.827			

Source	DF	Seq SS
B	1	11.147
C	1	81.796
G_0	1	11.907
C*C	1	14.384
B*C	1	22.334

Unusual Observations

Obs	B	R1	Fit	SE Fit	Residual	St Resid
14	90.0	9.000	5.152	0.499	3.848	3.04R
20	60.0	*	7.619	0.886	*	* X
22	60.0	*	6.723	0.879	*	* X
36	60.0	*	6.723	0.879	*	* X
38	60.0	*	7.619	0.886	*	* X
41	60.0	7.000	6.723	0.879	0.277	0.27 X
42	60.0	*	7.619	0.886	*	* X
48	60.0	*	7.619	0.886	*	* X
76	60.0	*	7.619	0.886	*	* X
78	60.0	*	6.723	0.879	*	* X
81	60.0	5.000	7.614	0.421	-2.614	-2.02R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Regression analysis: R3 versus C, D, C*C, C*D

The regression equation is
R3 = 3.83 + 0.105 C + 15.5 D - 0.000458 C*C - 0.189 C*D

53 cases used, 36 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	3.8299	0.7567	5.06	0.000
C	0.10542	0.02585	4.08	0.000
D	15.542	3.436	4.52	0.000
C*C	-0.0004578	0.0001993	-2.30	0.026
C*D	-0.18884	0.08563	-2.21	0.032

S = 1.28318   R-Sq = 50.1%   R-Sq(adj) = 46.0%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	4	79.418	19.855	12.06	0.000
Residual Error	48	79.034	1.647		
Total	52	158.453			

Source	DF	Seq SS
C	1	28.151
D	1	31.212
C*C	1	12.048
C*D	1	8.007

Unusual Observations

Obs	C	R3	Fit	SE Fit	Residual	St Resid
20	100	*	9.460	1.001	*	* X
21	10	3.000	7.569	0.247	-4.569	-3.63R
25	100	*	9.460	1.001	*	* X
32	100	*	9.460	1.001	*	* X
35	100	*	9.460	1.001	*	* X
40	100	*	9.460	1.001	*	* X
48	100	*	9.460	1.001	*	* X
62	100	*	9.460	1.001	*	* X
72	100	*	9.460	1.001	*	* X
76	100	*	9.460	1.001	*	* X
78	100	*	9.460	1.001	*	* X
86	100	6.000	9.125	0.515	-3.125	-2.66R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Regression analysis: R4 versus E_1

The regression equation is
R4 = 0.0235 + 0.00897 E_1

53 cases used, 36 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	0.023456	0.001795	13.07	0.000
E_1	0.008965	0.002998	2.99	0.004

S = 0.0104650   R-Sq = 14.9%   R-Sq(adj) = 13.3%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	0.0009797	0.0009797	8.95	0.004
Residual Error	51	0.0055853	0.0001095		
Total	52	0.0065650			

Unusual Observations

Obs	E_1	R4	Fit	SE Fit	Residual	St Resid
46	1.00	0.07250	0.03242	0.00240	0.04008	3.93R
70	1.00	0.01200	0.03242	0.00240	-0.02042	-2.00R

R denotes an observation with a large standardized residual.

Regression analysis: R6 versus B, C, F, E_2, C*C, B*F

```
The regression equation is
R6 = - 1.01 + 0.0403 B + 0.200 C + 1.69 F + 1.21 E_2 - 0.00133 C*C - 0.0234 B*F


53 cases used, 36 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant       -1.014      2.736  -0.37  0.713
B             0.04030    0.03482   1.16  0.253
C             0.19992    0.03011   6.64  0.000
F               1.689      1.017   1.66  0.103
E_2            1.2064     0.5486   2.20  0.033
C*C        -0.0013279  0.0002906  -4.57  0.000
B*F          -0.02335    0.01376  -1.70  0.097


S = 1.79495   R-Sq = 70.6%   R-Sq(adj) = 66.8%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       6  356.662  59.444  18.45  0.000
Residual Error  46  148.206   3.222
Total           52  504.868


Source  DF   Seq SS
B        1    3.962
C        1  255.739
F        1    0.508
E_2      1   27.094
C*C      1   60.083
B*F      1    9.275


Unusual Observations

Obs     B      R6    Fit  SE Fit  Residual  St Resid
 26  75.0   8.000  3.875   0.481     4.125     2.39R
 53  90.0  10.000  5.686   0.807     4.314     2.69R
 55  60.0   8.000  4.423   0.661     3.577     2.14R

R denotes an observation with a large standardized residual.
```

Regression analysis: R7 versus A, B, C, E_2, C*C, A*C

```
The regression equation is
R7 = 3.63 - 0.0384 A + 0.0154 B + 0.134 C + 1.30 E_2 - 0.00132 C*C
     + 0.000862 A*C


53 cases used, 36 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant        3.629      1.879   1.93  0.060
A            -0.03842    0.02257  -1.70  0.095
```

```
B              0.01541    0.01939   0.79  0.431
C              0.13407    0.03533   3.79  0.000
E_2             1.2998     0.4872   2.67  0.011
C*C         -0.0013167  0.0002576  -5.11  0.000
A*C          0.0008617  0.0004152   2.08  0.044


S = 1.59118   R-Sq = 72.8%   R-Sq(adj) = 69.3%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       6  311.837  51.973  20.53  0.000
Residual Error  46  116.465   2.532
Total           52  428.302


Source  DF   Seq SS
A        1   10.823
B        1    1.347
C        1  200.861
E_2      1   28.574
C*C      1   59.327
A*C      1   10.905


Unusual Observations

Obs     A     R7    Fit  SE Fit  Residual  St Resid
  9  40.0  8.000  6.935   1.042     1.065      0.89 X
 13  40.0  8.000  7.166   1.041     0.834      0.69 X
 20  40.0      *  6.704   1.121         *         * X
 30  40.0      *  8.235   1.080         *         * X
 38  40.0      *  8.003   1.149         *         * X
 40  40.0      *  7.166   1.041         *         * X
 53  80.0  9.000  5.141   0.677     3.859      2.68R
 59  40.0      *  6.935   1.042         *         * X
 62  40.0      *  8.235   1.080         *         * X
 69  40.0      *  6.935   1.042         *         * X
 72  40.0      *  8.235   1.080         *         * X
 78  40.0      *  6.704   1.121         *         * X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

Regression analysis: R8 versus C, D, F, E_1, E_2, C*D, C*F

```
The regression equation is
R8 = 4.05 - 0.000533 C - 0.283 D - 0.00280 F - 0.0210 E_1 + 0.0114 E_2
     + 0.00305 C*D + 0.000086 C*F


53 cases used, 36 cases contain missing values


Predictor        Coef     SE Coef       T      P
Constant      4.05247     0.01433  282.80  0.000
C          -0.0005333   0.0003491   -1.53  0.134
D            -0.28270     0.05528   -5.11  0.000
F           -0.002803    0.002688   -1.04  0.303
```

```
E_1         -0.020985    0.006958   -3.02  0.004
E_2          0.011440    0.007231    1.58  0.121
C*D          0.003046    0.001372    2.22  0.031
C*F        0.00008577  0.00005231    1.64  0.108


S = 0.0205637   R-Sq = 58.5%   R-Sq(adj) = 52.0%


Analysis of Variance

Source          DF         SS         MS     F      P
Regression       7  0.0268287  0.0038327  9.06  0.000
Residual Error  45  0.0190289  0.0004229
Total           52  0.0458576


Source  DF     Seq SS
C        1  0.0031898
D        1  0.0100989
F        1  0.0001234
E_1      1  0.0095199
E_2      1  0.0010262
C*D      1  0.0017335
C*F      1  0.0011369


Unusual Observations

Obs    C       R8      Fit   SE Fit  Residual  St Resid
 15   10  3.87224  3.94659  0.00727  -0.07435     -3.86R
 20  100        *  3.99190  0.01511         *         * X
 25  100        *  4.02443  0.01630         *         * X
 32  100        *  4.02432  0.01576         *         * X
 35  100        *  4.01278  0.01784         *         * X
 40  100        *  4.02443  0.01630         *         * X
 48  100        *  4.01288  0.01570         *         * X
 62  100        *  4.01278  0.01784         *         * X
 72  100        *  4.01278  0.01784         *         * X
 76  100        *  4.03587  0.01681         *         * X
 78  100        *  4.00134  0.01821         *         * X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

Regression analysis: R10 versus A, D, F, E_1, E_2, G_0, D*D, A*F

```
The regression equation is
R10 = 13.2 + 0.0923 A - 109 D + 1.78 F - 4.86 E_1 - 5.23 E_2 - 1.53 G_0
      + 248 D*D - 0.0244 A*F


77 cases used, 12 cases contain missing values


Predictor      Coef  SE Coef      T      P
Constant     13.206    4.374   3.02  0.004
A           0.09231  0.04403   2.10  0.040
D           -108.77    38.21  -2.85  0.006
F             1.781    1.151   1.55  0.126
E_1          -4.863    1.145  -4.25  0.000
E_2          -5.229    1.060  -4.93  0.000
```

G_0	-1.5256	0.9085	-1.68	0.098
D*D	248.34	94.58	2.63	0.011
A*F	-0.02445	0.01749	-1.40	0.167

S = 3.94022   R-Sq = 39.4%   R-Sq(adj) = 32.3%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	8	686.95	85.87	5.53	0.000
Residual Error	68	1055.72	15.53		
Total	76	1742.68			

Source	DF	Seq SS
A	1	45.02
D	1	18.23
F	1	7.72
E_1	1	77.24
E_2	1	373.65
G_0	1	35.95
D*D	1	98.78
A*F	1	30.35

Unusual Observations

Obs	A	R10	Fit	SE Fit	Residual	St Resid
51	80.0	18.000	8.771	1.436	9.229	2.52R
52	80.0	19.000	10.311	1.404	8.689	2.36R
58	80.0	20.000	10.672	1.505	9.328	2.56R
61	80.0	1.000	9.961	1.138	-8.961	-2.38R
82	80.0	4.000	11.847	1.254	-7.847	-2.10R

R denotes an observation with a large standardized residual.

Regression analysis: R11 versus A, B, C, F, D, A*B, A*C, A*D, A*F, B*F

The regression equation is
R11 = - 80.4 + 1.60 A + 0.667 B - 0.259 C - 4.91 F + 149 D - 0.0165 A*B
      + 0.00635 A*C - 2.17 A*D - 0.0917 A*F + 0.161 B*F

52 cases used, 37 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	-80.42	34.70	-2.32	0.026
A	1.6024	0.5396	2.97	0.005
B	0.6673	0.4259	1.57	0.125
C	-0.2586	0.1561	-1.66	0.105
F	-4.905	4.999	-0.98	0.332
D	149.02	73.32	2.03	0.049
A*B	-0.016527	0.006389	-2.59	0.013
A*C	0.006354	0.002270	2.80	0.008
A*D	-2.172	1.104	-1.97	0.056
A*F	-0.09168	0.04861	-1.89	0.066
B*F	0.16077	0.06933	2.32	0.025

```
S = 8.21980   R-Sq = 52.2%   R-Sq(adj) = 40.5%


Analysis of Variance

Source          DF       SS      MS     F      P
Regression      10  3024.19  302.42  4.48  0.000
Residual Error  41  2770.17   67.57
Total           51  5794.36


Source  DF   Seq SS
A        1    91.42
B        1    58.27
C        1  1702.98
F        1    68.72
D        1    11.33
A*B      1   183.91
A*C      1   336.12
A*D      1   116.19
A*F      1    91.95
B*F      1   363.30


Unusual Observations

Obs     A     R11     Fit  SE Fit  Residual  St Resid
 14  40.0   14.50    2.83    6.33     11.67      2.22R
 20  40.0       *   -8.04    7.62         *         * X
 21  60.0  -23.00   -0.37    2.50    -22.63     -2.89R
 38  40.0       *   -3.97    7.03         *         * X
 40  40.0       *   13.59    7.10         *         * X
 55  60.0   12.50   -3.68    3.43     16.18      2.17R
 56  40.0       *   26.22    6.98         *         * X
 62  40.0       *  -10.09    7.68         *         * X
 72  40.0       *  -10.09    7.68         *         * X
 78  40.0       *  -10.18    8.20         *         * X
 79  40.0   19.00    0.73    4.17     18.27      2.58R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

Regression analysis: R12 versus A, B, D, F, A*D, B*F

```
The regression equation is
R12 = - 16.8 + 0.614 A - 0.458 B + 211 D - 11.4 F - 2.35 A*D + 0.164 B*F


53 cases used, 36 cases contain missing values


Predictor      Coef  SE Coef      T      P
Constant     -16.84    25.34  -0.66  0.510
A            0.6145   0.3300   1.86  0.069
B           -0.4583   0.2183  -2.10  0.041
D            210.59    99.21   2.12  0.039
F           -11.440    6.491  -1.76  0.085
A*D          -2.350    1.473  -1.60  0.118
B*F         0.16402  0.08793   1.87  0.069
```

```
S = 11.6433   R-Sq = 25.2%   R-Sq(adj) = 15.5%


Analysis of Variance

Source          DF      SS     MS     F      P
Regression       6  2102.7  350.5  2.59  0.030
Residual Error  46  6236.1  135.6
Total           52  8338.8


Source  DF  Seq SS
A        1   194.2
B        1   184.2
D        1   996.1
F        1    42.7
A*D      1   213.7
B*F      1   471.8


Unusual Observations

Obs     A     R12    Fit  SE Fit  Residual  St Resid
 21  60.0  -39.00  -0.66    2.87    -38.34     -3.40R

R denotes an observation with a large standardized residual.
```

Regression analysis: R15 versus B, C, F, E_1, C*C, B*C, B*F

```
The regression equation is
R15 = 9.85 - 0.0287 B - 0.0197 C + 0.867 F - 0.679 E_1 - 0.000283 C*C
      + 0.000871 B*C - 0.0114 B*F


53 cases used, 36 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant        9.849      2.349   4.19  0.000
B            -0.02867    0.03031  -0.95  0.349
C            -0.01971    0.03764  -0.52  0.603
F              0.8668     0.7081   1.22  0.227
E_1           -0.6792     0.3680  -1.85  0.072
C*C        -0.0002835  0.0002067  -1.37  0.177
B*C         0.0008714  0.0004773   1.83  0.075
B*F         -0.011376   0.009537  -1.19  0.239


S = 1.21476   R-Sq = 38.0%   R-Sq(adj) = 28.3%


Analysis of Variance

Source          DF       SS     MS     F      P
Regression       7   40.615  5.802  3.93  0.002
Residual Error  45   66.403  1.476
Total           52  107.019


Source  DF  Seq SS
```

B	1	4.767
C	1	17.952
F	1	0.706
E_1	1	8.587
C*C	1	0.607
B*C	1	5.898
B*F	1	2.100

Unusual Observations

Obs	B	R15	Fit	SE Fit	Residual	St Resid
36	60.0	*	9.288	0.889	*	* X
38	60.0	*	8.551	0.829	*	* X
46	75.0	4.000	7.448	0.370	-3.448	-2.98R
47	90.0	5.000	7.514	0.423	-2.514	-2.21R
60	90.0	9.000	6.520	0.558	2.480	2.30R
64	75.0	10.000	7.475	0.316	2.525	2.15R
76	60.0	*	9.288	0.889	*	* X
78	60.0	*	8.551	0.829	*	* X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Regression analysis: R9 versus A, G_0, A*A

The regression equation is
R9 = 6.57 - 0.0226 A + 0.0465 G_0 + 0.000188 A*A

53 cases used, 36 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	6.5703	0.2735	24.02	0.000
A	-0.022581	0.009424	-2.40	0.020
G_0	0.04650	0.02776	1.67	0.100
A*A	0.00018828	0.00007643	2.46	0.017

S = 0.100423   R-Sq = 14.7%   R-Sq(adj) = 9.4%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	0.08493	0.02831	2.81	0.049
Residual Error	49	0.49415	0.01008		
Total	52	0.57909			

Source	DF	Seq SS
A	1	0.00360
G_0	1	0.02013
A*A	1	0.06121

Unusual Observations

Obs	A	R9	Fit	SE Fit	Residual	St Resid
5	60.0	5.2569	5.8933	0.0293	-0.6364	-6.63R

```
R denotes an observation with a large standardized residual.
```

4 Regression Analysis

Regression analysis: R7 versus C, F, E_1, C*C, B*C, B*F

```
The regression equation is
R7 = 3.28 + 0.162 C + 0.279 F - 0.426 E_1 - 0.00128 C*C + 0.000342 B*C
     - 0.00648 B*F


53 cases used, 36 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant       3.2846     0.6636   4.95  0.000
C             0.16241    0.04061   4.00  0.000
F              0.2788     0.7285   0.38  0.704
E_1           -0.4257     0.5246  -0.81  0.421
C*C        -0.0012791  0.0002944  -4.35  0.000
B*C         0.0003417  0.0005320   0.64  0.524
B*F         -0.006480   0.009836  -0.66  0.513


S = 1.73484   R-Sq = 67.7%   R-Sq(adj) = 63.5%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       6  289.857  48.310  16.05  0.000
Residual Error  46  138.444   3.010
Total           52  428.302


Source  DF   Seq SS
C        1  210.230
F        1    6.752
E_1      1   11.909
C*C      1   59.307
B*C      1    0.354
B*F      1    1.306


Unusual Observations

Obs    C     R7    Fit  SE Fit  Residual  St Resid
  7   10  9.000  4.623   0.406     4.377     2.60R
 36  100      *  8.345   1.120         *         * X
 38  100      *  8.785   1.183         *         * X
 41  100  9.000  8.359   1.149     0.641      0.49 X
 42  100      *  8.359   1.149         *         * X
 51   10  1.000  5.037   0.503    -4.037    -2.43R
 53   10  9.000  5.088   0.511     3.912     2.36R
 76  100      *  8.345   1.120         *         * X
 78  100      *  8.785   1.183         *         * X
 79   10  8.000  4.546   0.630     3.454     2.14R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

5 Regression Analysis

Regression analysis: R7 versus C, C*C

```
The regression equation is
R7 = 2.72 + 0.189 C - 0.00129 C*C


53 cases used, 36 cases contain missing values


Predictor        Coef    SE Coef      T      P
Constant       2.7201     0.4980   5.46  0.000
C             0.18901    0.02716   6.96  0.000
C*C        -0.0012872  0.0002628  -4.90  0.000


S = 1.71669   R-Sq = 65.6%   R-Sq(adj) = 64.2%


Analysis of Variance

Source          DF      SS      MS      F      P
Regression       2  280.95  140.48  47.67  0.000
Residual Error  50  147.35    2.95
Total           52  428.30


Source  DF  Seq SS
C        1  210.23
C*C      1   70.72


Unusual Observations

Obs   C      R7    Fit  SE Fit  Residual  St Resid
  7  10  9.000  4.481   0.330     4.519      2.68R
 51  10  1.000  4.481   0.330    -3.481     -2.07R
 53  10  9.000  4.481   0.330     4.519      2.68R
 79  10  8.000  4.481   0.330     3.519      2.09R

R denotes an observation with a large standardized residual.
```

Regression analysis: R17 versus A, B, C, D, E_1, E_2, F, G_0

```
The regression equation is
R17 = 6.72 + 0.0596 A - 0.0368 B - 0.0363 C + 6.87 D + 0.883 E_1 + 0.814 E_2
      + 0.315 F + 0.010 G_0


89 cases used, 1 cases contain missing values


Predictor       Coef   SE Coef      T      P
Constant       6.723     1.967   3.42  0.001
A            0.05964   0.01532   3.89  0.000
B           -0.03678   0.02056  -1.79  0.077
C          -0.036283  0.006813  -5.33  0.000
D              6.871     3.097   2.22  0.029
E_1           0.8833    0.6046   1.46  0.148
```

E_2	0.8141	0.6123	1.33	0.187
F	0.3147	0.1532	2.05	0.043
G_0	0.0100	0.4975	0.02	0.984

S = 2.31823   R-Sq = 45.3%   R-Sq(adj) = 39.7%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	8	351.210	43.901	8.17	0.000
Residual Error	79	424.563	5.374		
Total	87	775.773			

Source	DF	Seq SS
A	1	109.558
B	1	19.231
C	1	158.182
D	1	29.258
E_1	1	3.510
E_2	1	8.713
F	1	22.756
G_0	1	0.002

Unusual Observations

Obs	A	R17	Fit	SE Fit	Residual	St Resid
13	40.0	10.000	5.067	0.735	4.933	2.24R
22	80.0	4.000	9.174	0.767	-5.174	-2.37R
82	80.0	2.000	7.505	0.710	-5.505	-2.49R

R denotes an observation with a large standardized residual.

Regression analysis: R18 versus A, B, C, D, E_1, E_2, F, G_0

The regression equation is
R18 = 7.09 + 0.0726 A - 0.0414 B - 0.0485 C + 6.91 D + 0.537 E_1 + 0.668 E_2
      + 0.040 F + 0.046 G_0

88 cases used, 1 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	7.094	1.988	3.57	0.001
A	0.07264	0.01548	4.69	0.000
B	-0.04144	0.02078	-1.99	0.050
C	-0.048532	0.006885	-7.05	0.000
D	6.915	3.130	2.21	0.030
E_1	0.5366	0.6109	0.88	0.382
E_2	0.6678	0.6187	1.08	0.284
F	0.0398	0.1548	0.26	0.798
G_0	0.0462	0.5027	0.09	0.927

S = 2.34274   R-Sq = 53.3%   R-Sq(adj) = 48.6%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	8	495.493	61.937	11.28	0.000
Residual Error	79	433.587	5.488		
Total	87	929.080			

Source	DF	Seq SS
A	1	156.922
B	1	27.084
C	1	276.415
D	1	27.455
E_1	1	0.844
E_2	1	6.348
F	1	0.377
G_0	1	0.046

Unusual Observations

Obs	A	R18	Fit	SE Fit	Residual	St Resid
8	80.0	2.000	8.070	0.770	-6.070	-2.74R
9	40.0	10.000	4.117	0.747	5.883	2.65R
13	40.0	10.000	3.462	0.742	6.538	2.94R

R denotes an observation with a large standardized residual.

Regression analysis: R17 versus A, B, C, D, E_1, E_2, F

The regression equation is
R17 = 6.73 + 0.0596 A - 0.0368 B - 0.0363 C + 6.87 D + 0.883 E_1 + 0.814 E_2
+ 0.315 F

88 cases used, 1 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	6.728	1.937	3.47	0.001
A	0.05964	0.01522	3.92	0.000
B	-0.03678	0.02043	-1.80	0.076
C	-0.036284	0.006770	-5.36	0.000
D	6.869	3.075	2.23	0.028
E_1	0.8827	0.6001	1.47	0.145
E_2	0.8144	0.6082	1.34	0.184
F	0.3148	0.1520	2.07	0.042

S = 2.30371   R-Sq = 45.3%   R-Sq(adj) = 40.5%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	7	351.208	50.173	9.45	0.000
Residual Error	80	424.565	5.307		
Total	87	775.773			

Source	DF	Seq SS
A	1	109.558
B	1	19.231
C	1	158.182
D	1	29.258
E_1	1	3.510
E_2	1	8.713
F	1	22.756

Unusual Observations

Obs	A	R17	Fit	SE Fit	Residual	St Resid
13	40.0	10.000	5.061	0.676	4.939	2.24R
22	80.0	4.000	9.169	0.720	-5.169	-2.36R
82	80.0	2.000	7.510	0.658	-5.510	-2.50R

R denotes an observation with a large standardized residual.

Regression analysis: R18 versus A, B, C, D

The regression equation is
R18 = 7.63 + 0.0728 A - 0.0421 B - 0.0485 C + 6.93 D

88 cases used, 1 cases contain missing values

Predictor	Coef	SE Coef	T	P
Constant	7.629	1.885	4.05	0.000
A	0.07277	0.01521	4.79	0.000
B	-0.04211	0.02028	-2.08	0.041
C	-0.048504	0.006747	-7.19	0.000
D	6.929	3.049	2.27	0.026

S = 2.30558   R-Sq = 52.5%   R-Sq(adj) = 50.2%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	4	487.88	121.97	22.95	0.000
Residual Error	83	441.20	5.32		
Total	87	929.08			

Source	DF	Seq SS
A	1	156.92
B	1	27.08
C	1	276.41
D	1	27.46

Unusual Observations

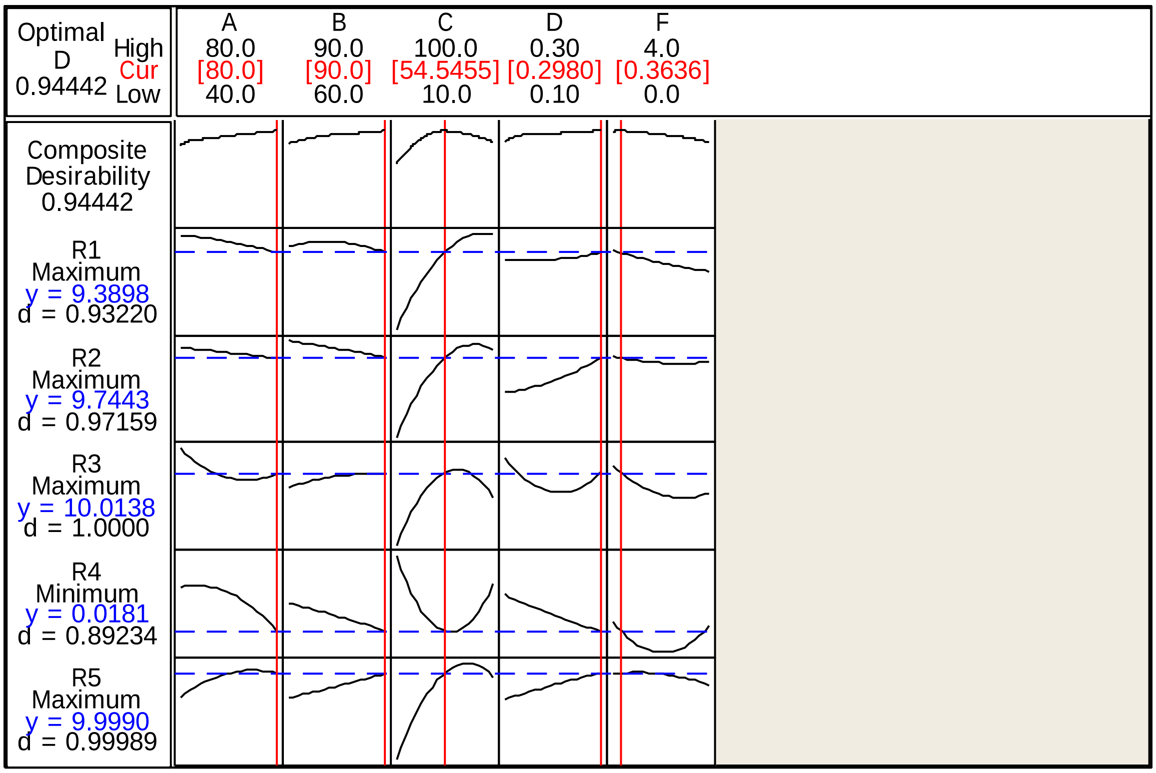
Obs	A	R18	Fit	SE Fit	Residual	St Resid
3	40.0	10.000	5.468	0.525	4.532	2.02R
8	80.0	2.000	7.686	0.571	-5.686	-2.55R
9	40.0	10.000	3.917	0.489	6.083	2.70R
13	40.0	10.000	3.285	0.591	6.715	3.01R

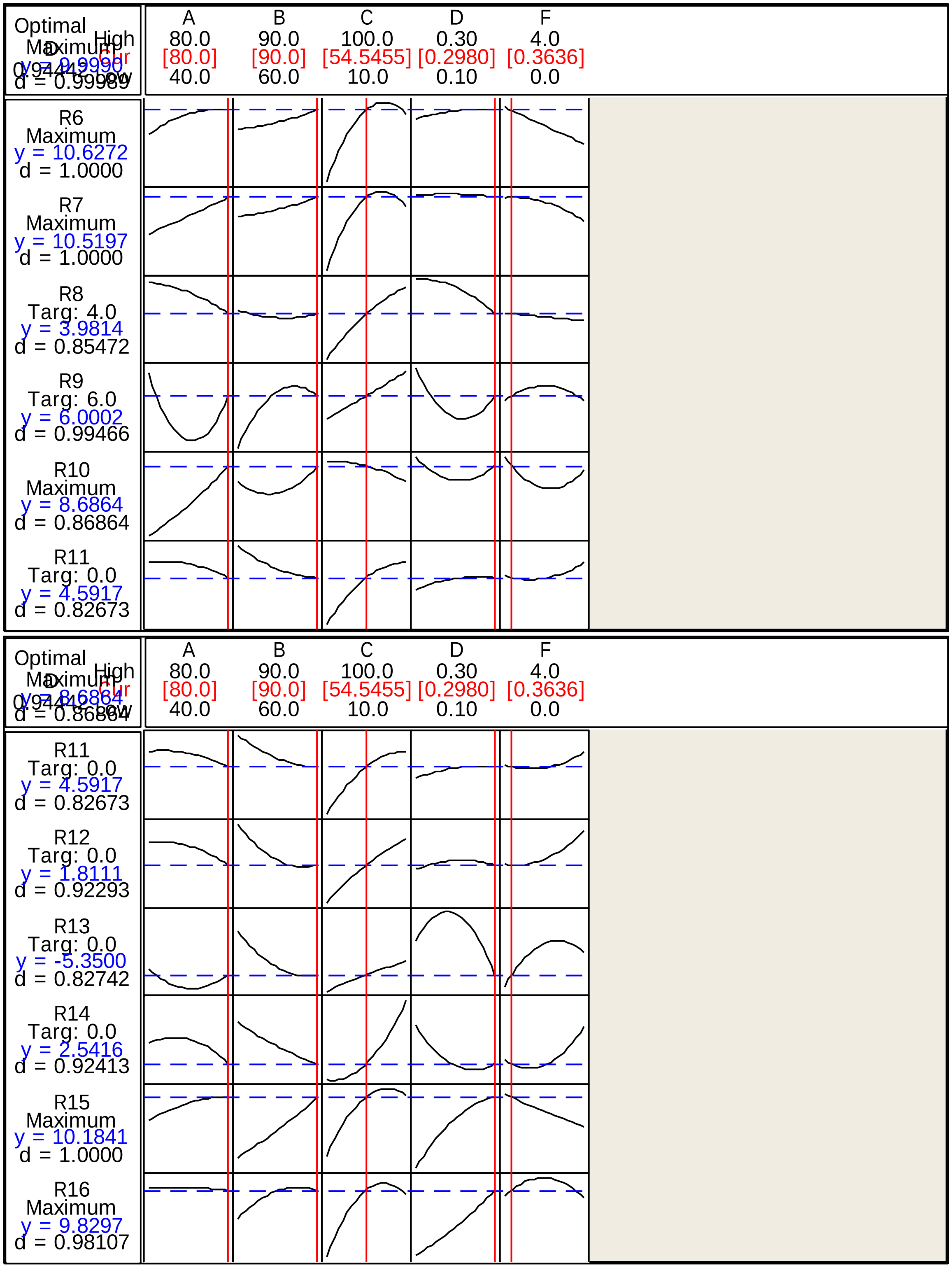
```
 82  80.0   3.000  7.686   0.571    -4.686     -2.10R

R denotes an observation with a large standardized residual
```

Appendix C

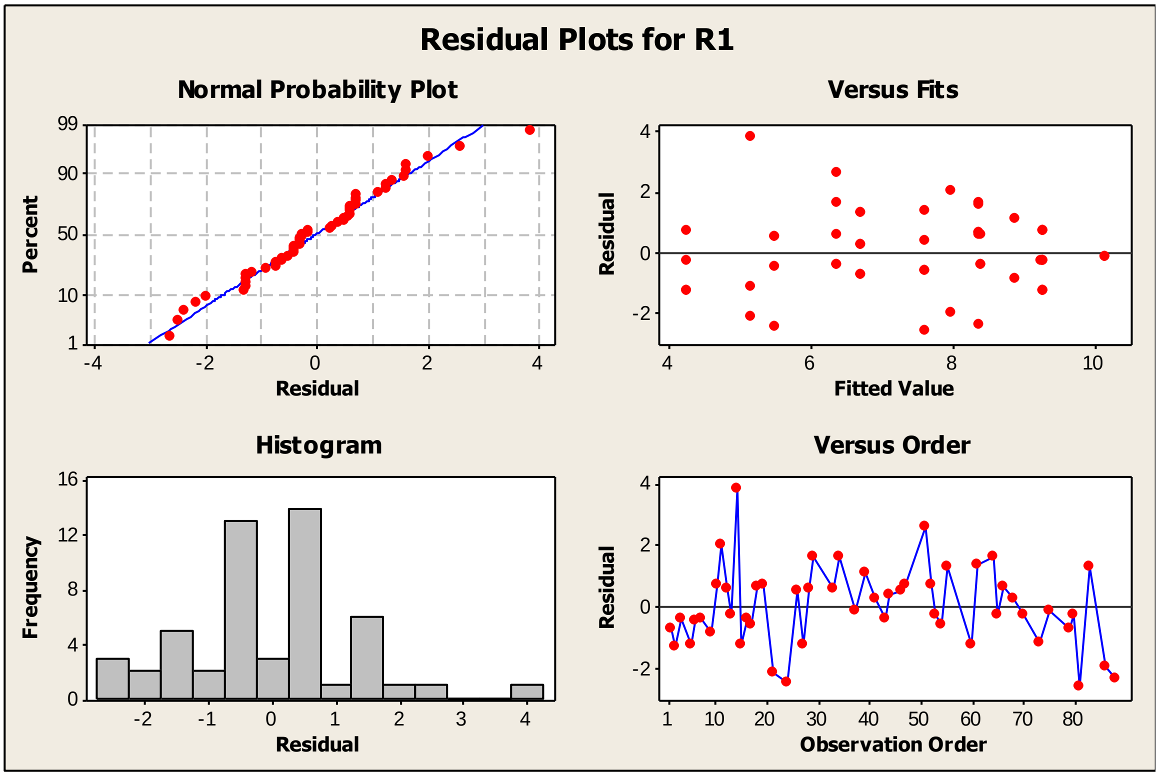
Optimization Plot

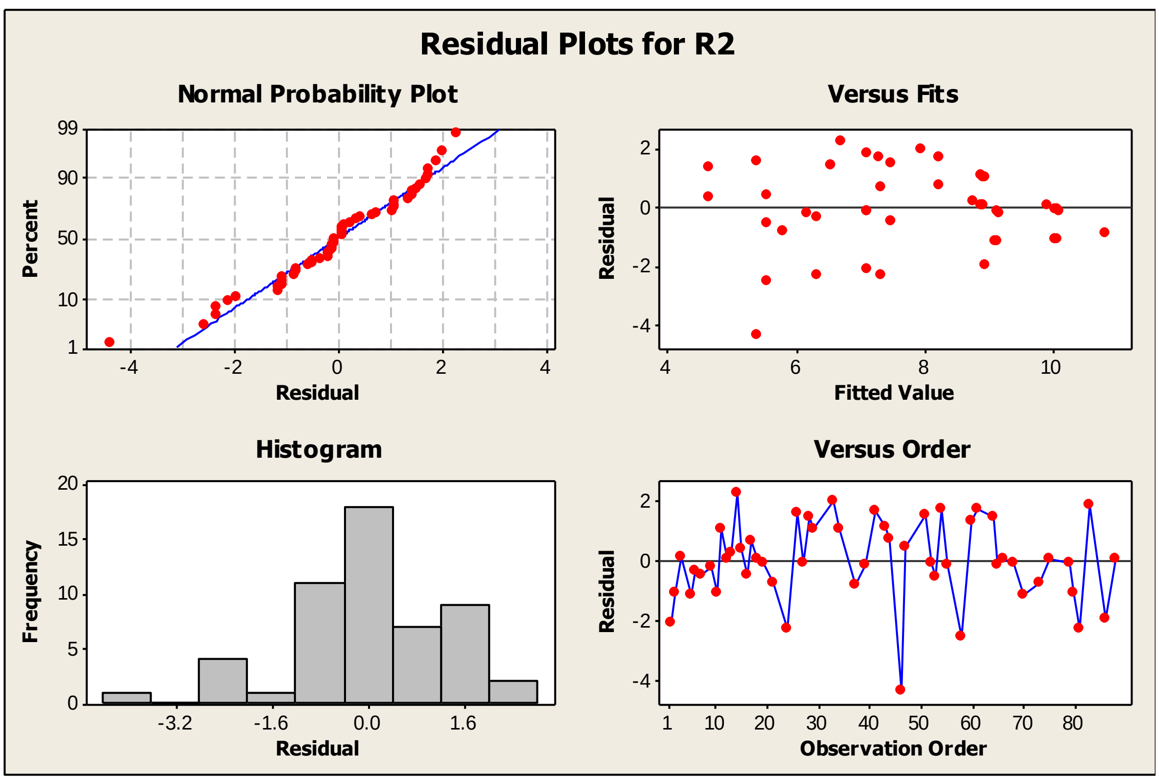


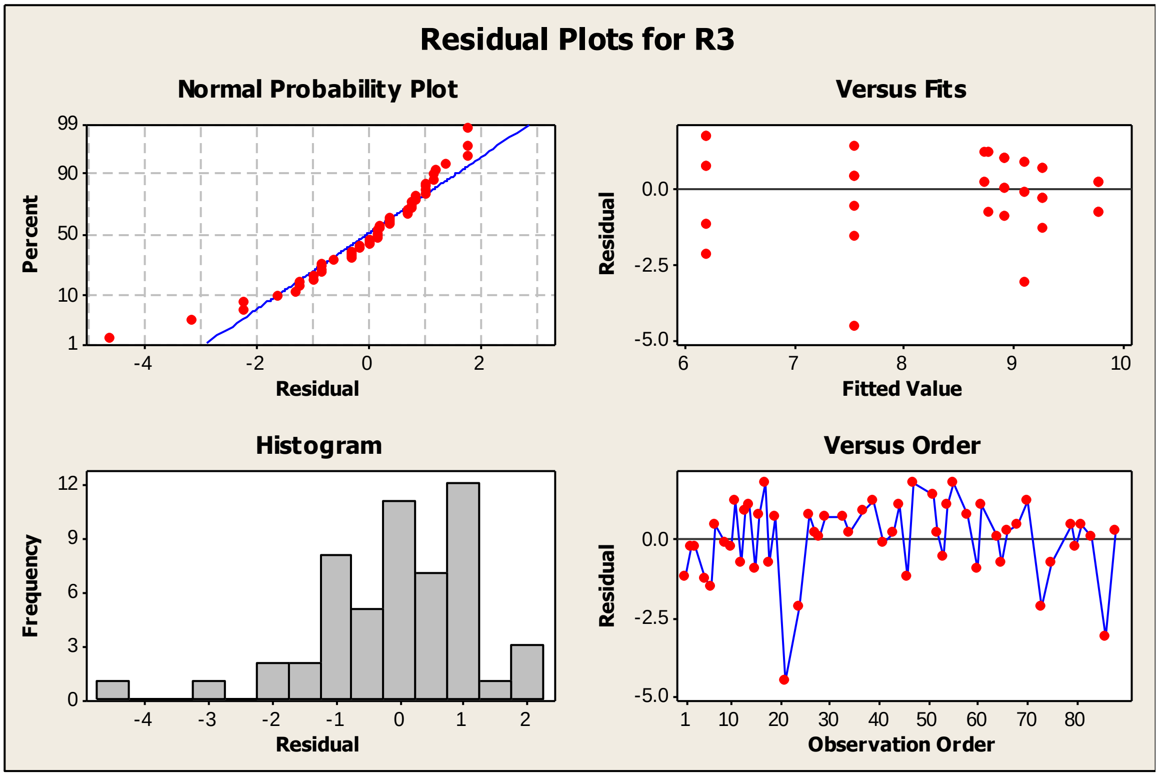

Optimal
High
Cur
Low
D
0.94413
Maximum
y = 9.9990
d = 0.99989
A
80.0
[80.0]
40.0
B
90.0
[90.0]
60.0
C
100.0
[54.5455]
10.0
D
0.30
[0.2980]
0.10
F
4.0
[0.3636]
0.0
R6
Maximum
y = 10.6272
d = 1.0000
R7
Maximum
y = 10.5197
d = 1.0000
R8
Targ: 4.0
y = 3.9814
d = 0.85472
R9
Targ: 6.0
y = 6.0002
d = 0.99466
R10
Maximum
y = 8.6864
d = 0.86864
R11
Targ: 0.0
y = 4.5917
d = 0.82673
Optimal
High
Cur
Low
D
0.94413
Maximum
y = 8.6864
d = 0.86864
R11
Targ: 0.0
y = 4.5917
d = 0.82673
R12
Targ: 0.0
y = 1.8111
d = 0.92293
R13
Targ: 0.0
y = -5.3500
d = 0.82742
R14
Targ: 0.0
y = 2.5416
d = 0.92413
R15
Maximum
y = 10.1841
d = 1.0000
R16
Maximum
y = 9.8297
d = 0.98107

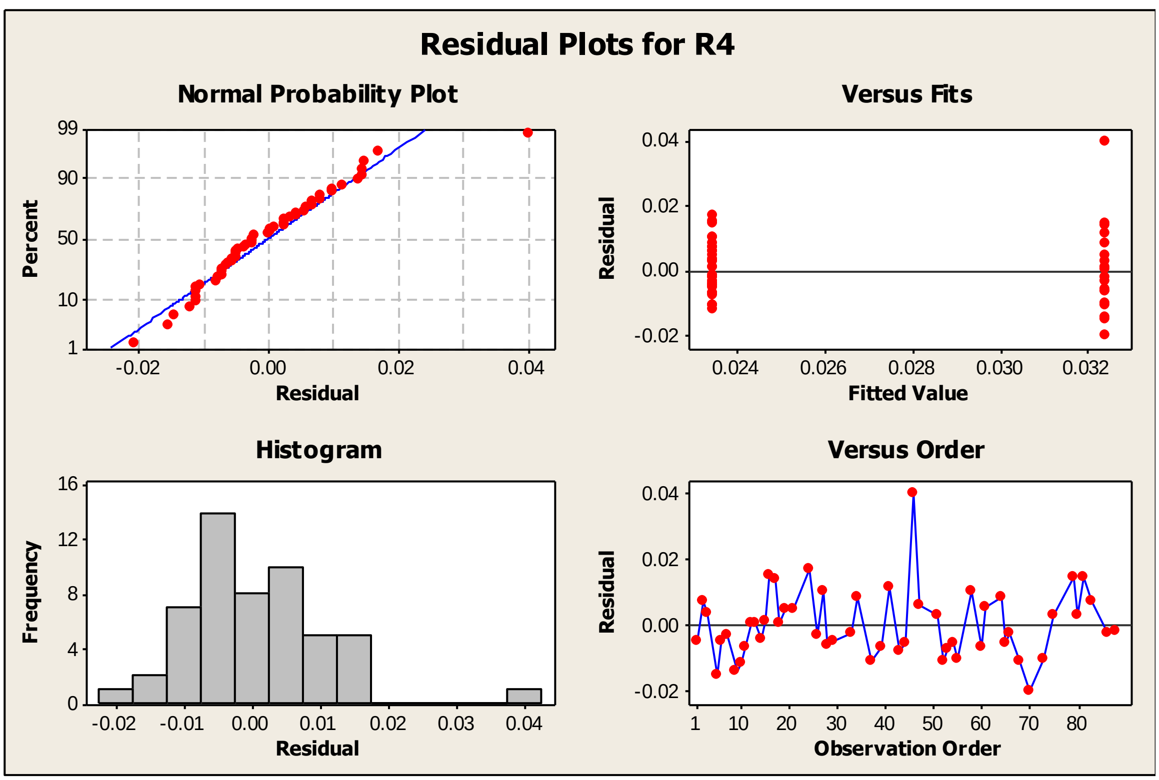
Appendix D

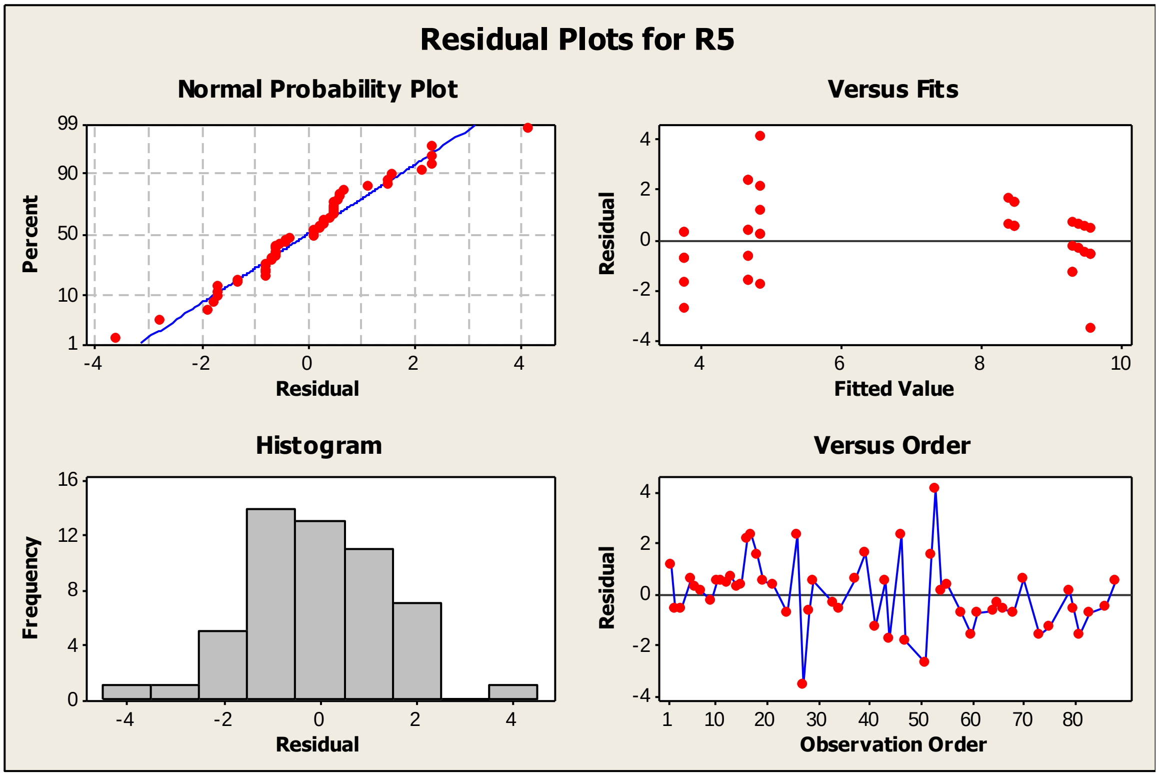
Residual Plots of the Responses

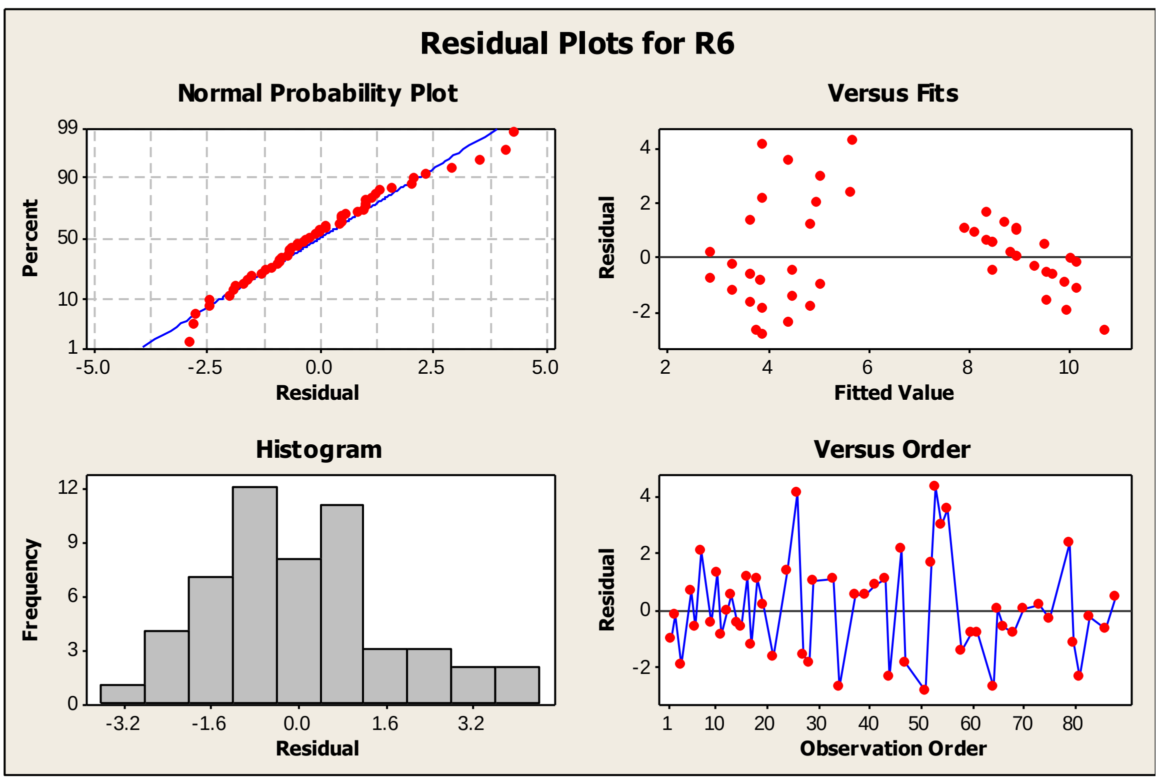


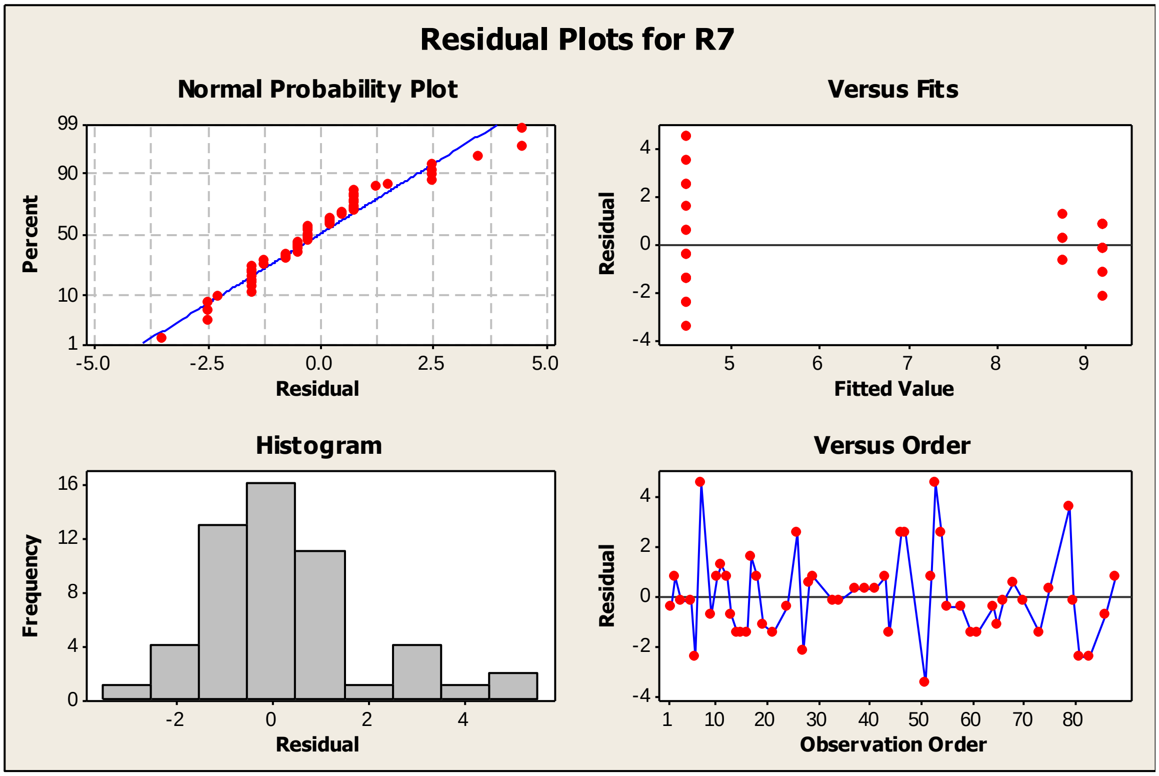


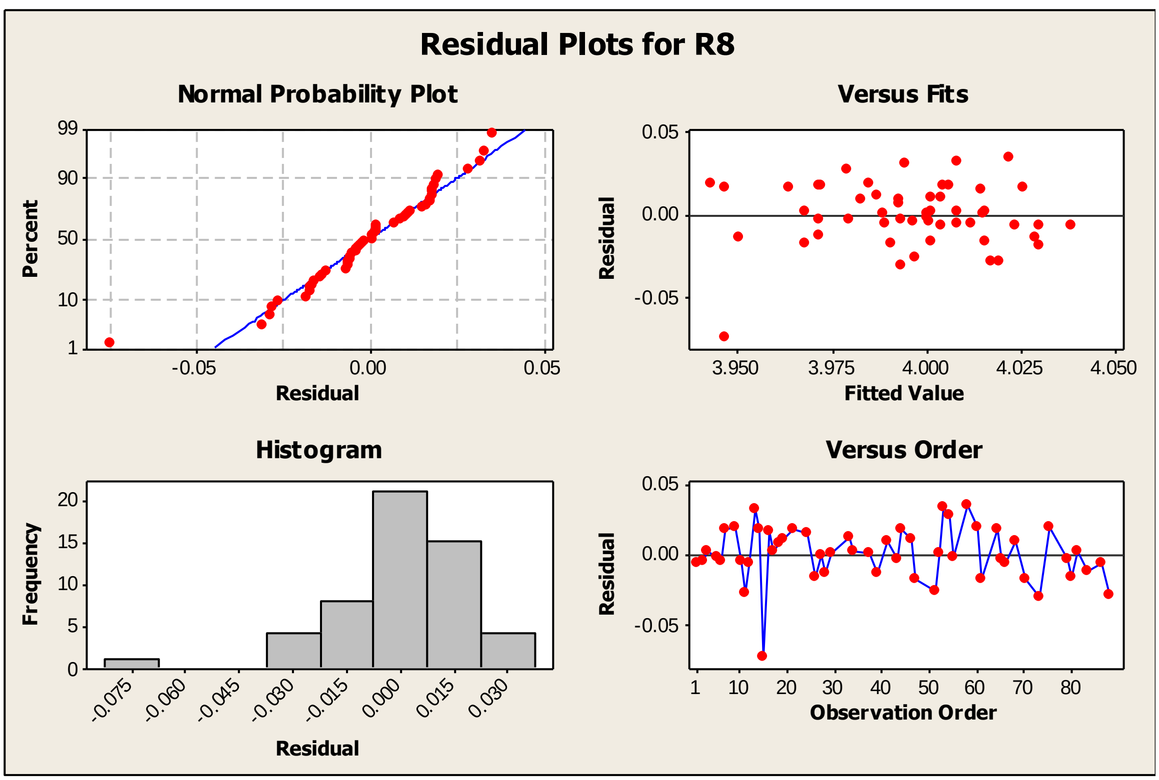

Residual Plots for R3
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

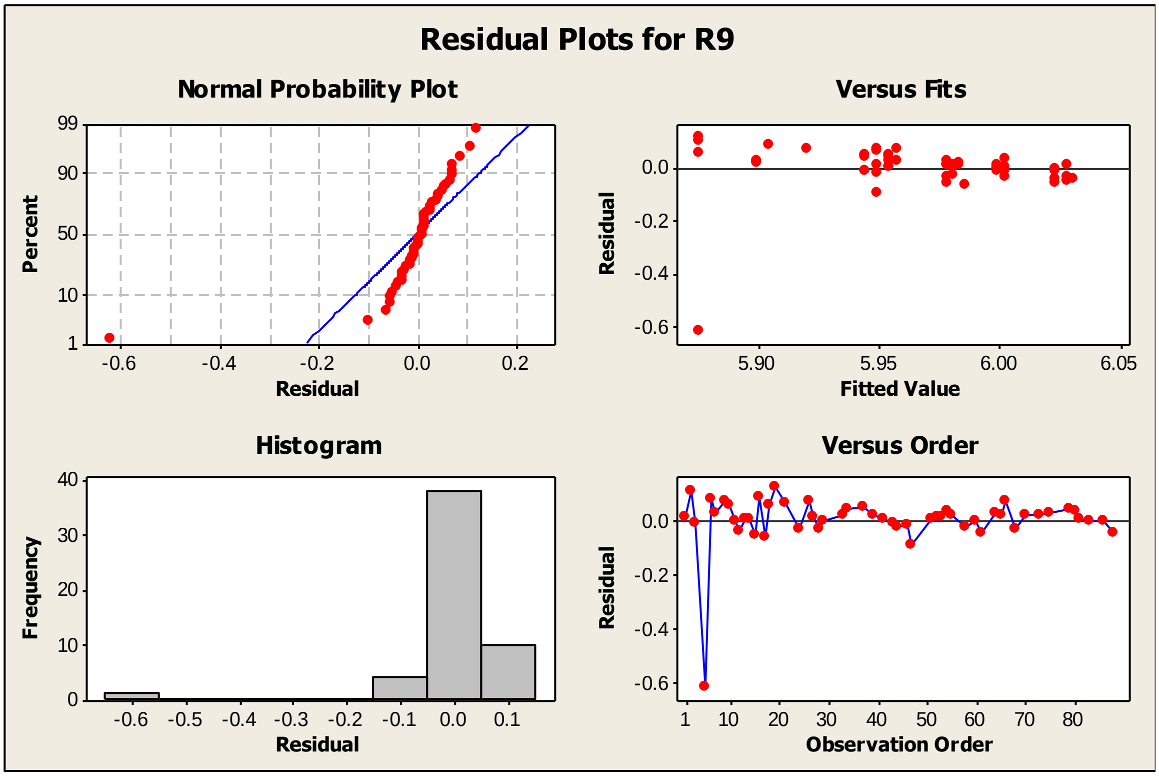

Residual Plots for R4
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

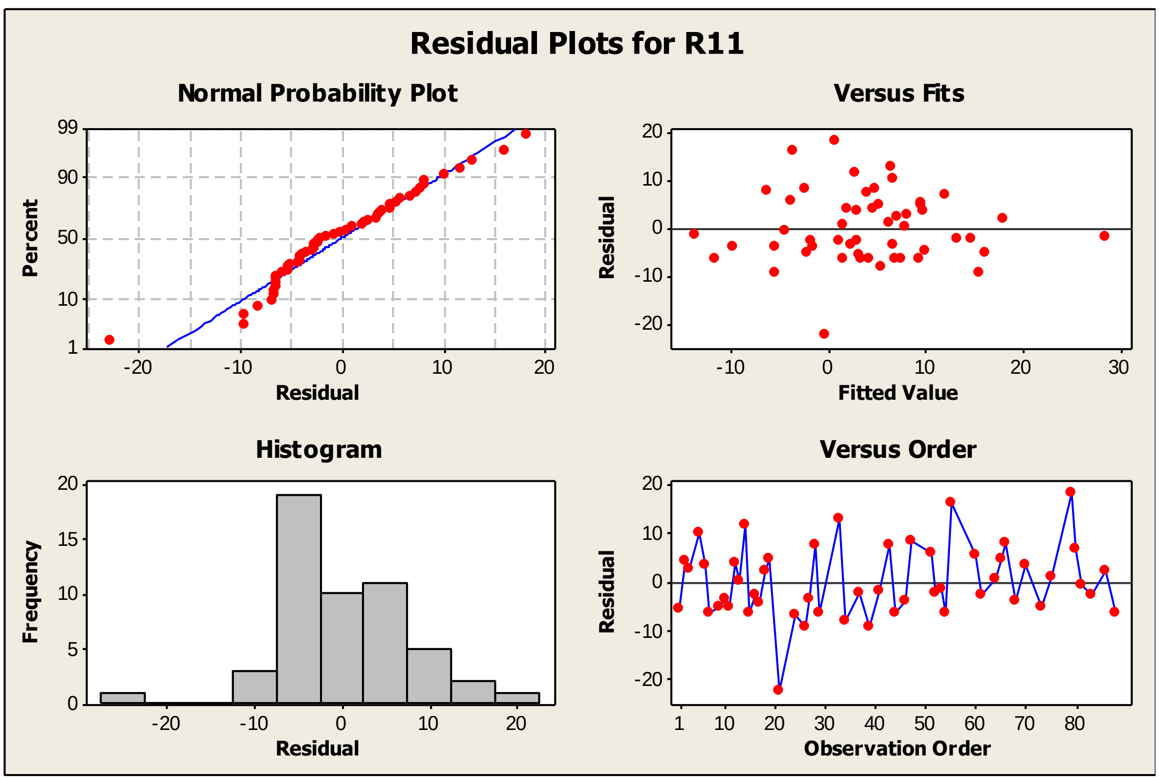

Residual Plots for R5
Normal Probability Plot
Versus Fits
Percent
Residual
Fitted Value
Histogram
Versus Order
Frequency
Observation Order

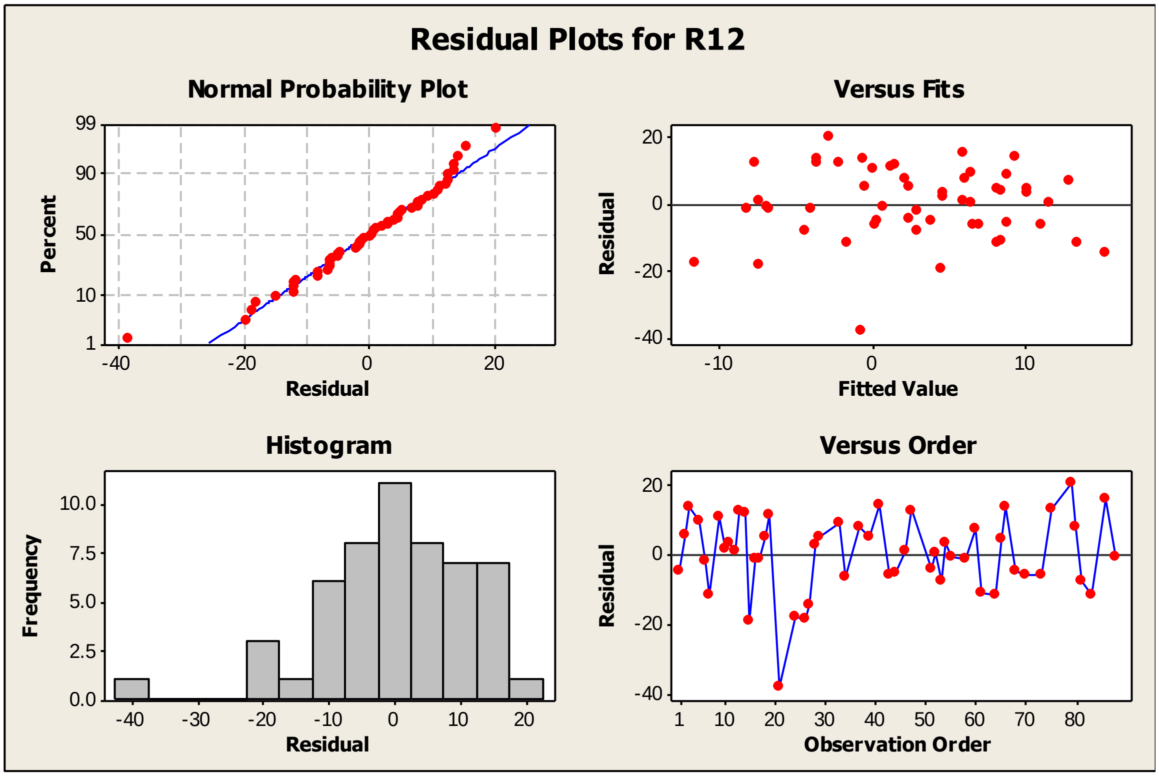

Residual Plots for R6
Normal Probability Plot
Versus Fits
Percent
Residual
Fitted Value
Histogram
Versus Order
Frequency
Observation Order

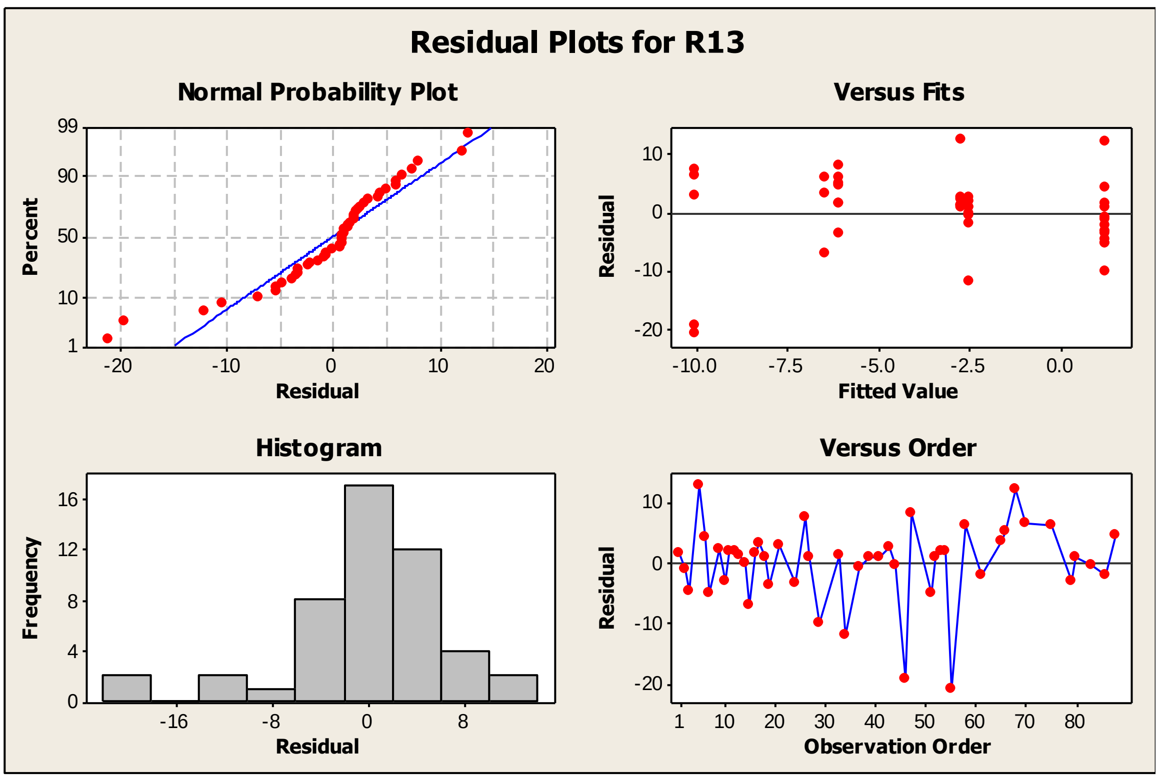

Residual Plots for R7
Normal Probability Plot
Versus Fits
Histogram
Versus Order
Percent
Residual
Fitted Value
Frequency
Observation Order

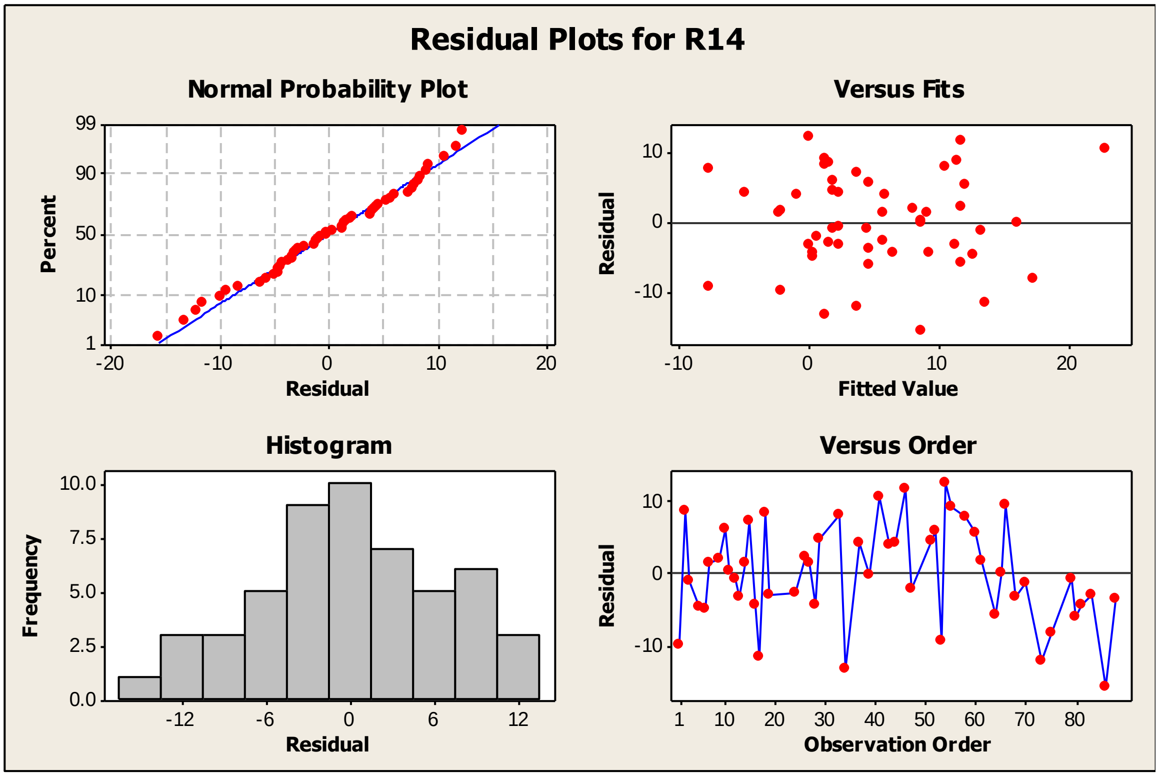

Residual Plots for R8
Normal Probability Plot
Versus Fits
Histogram
Versus Order
Percent
Residual
Fitted Value
Frequency
Observation Order

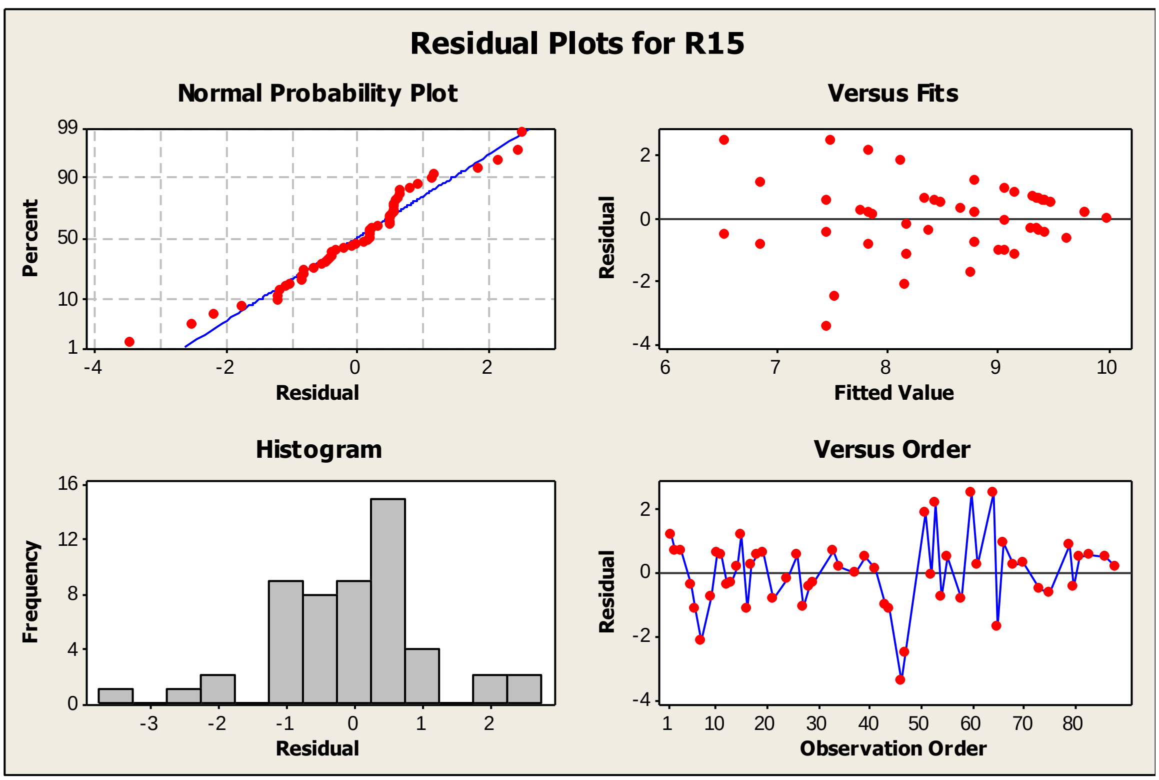

Residual Plots for R9
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

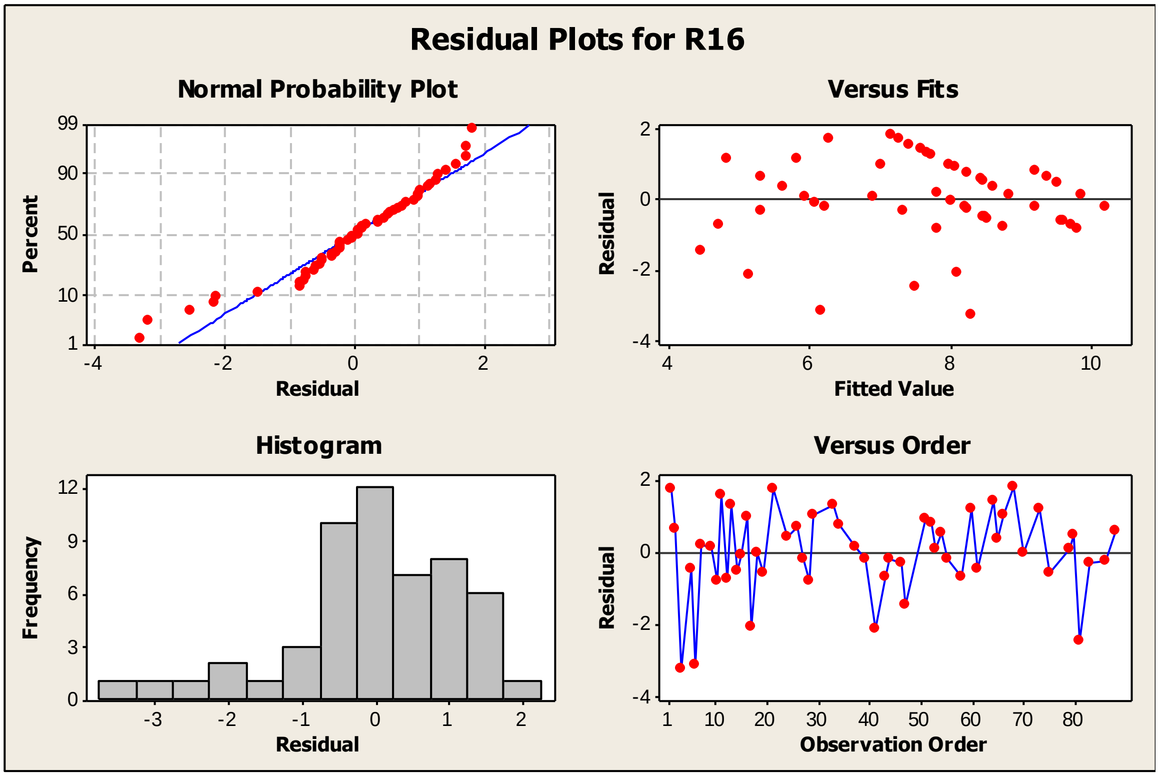

Residual Plots for R11
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

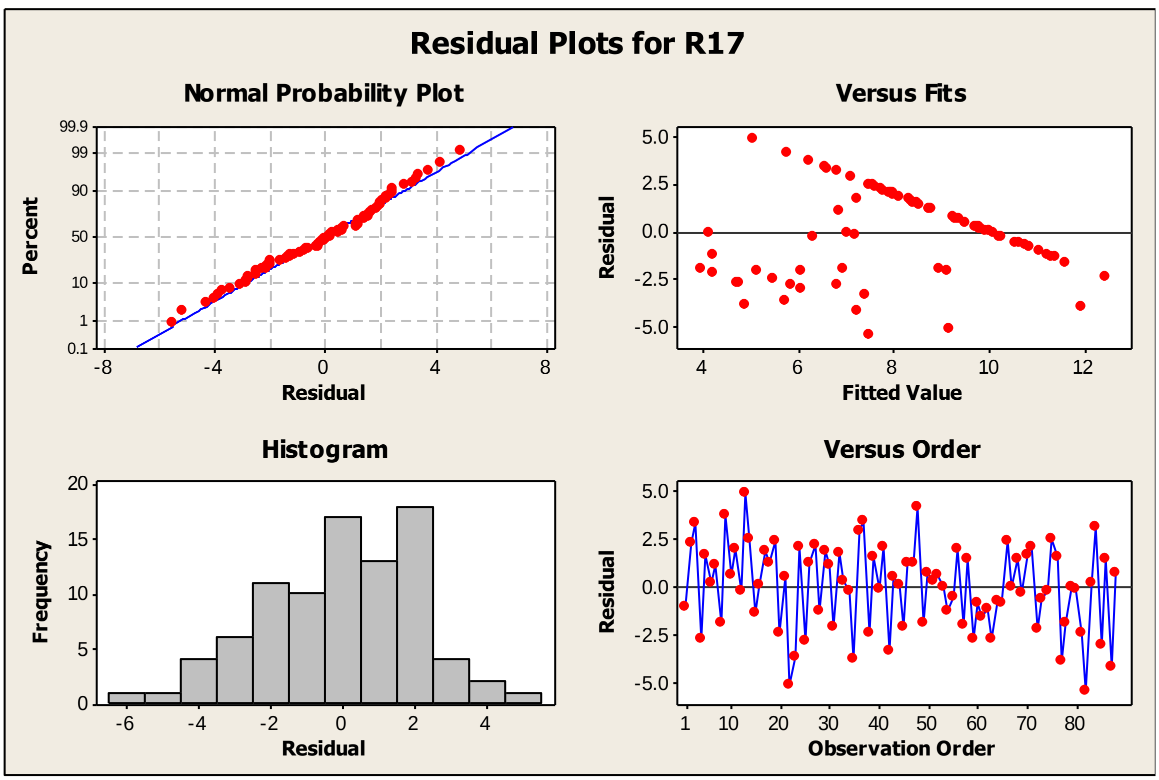

Residual Plots for R12
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

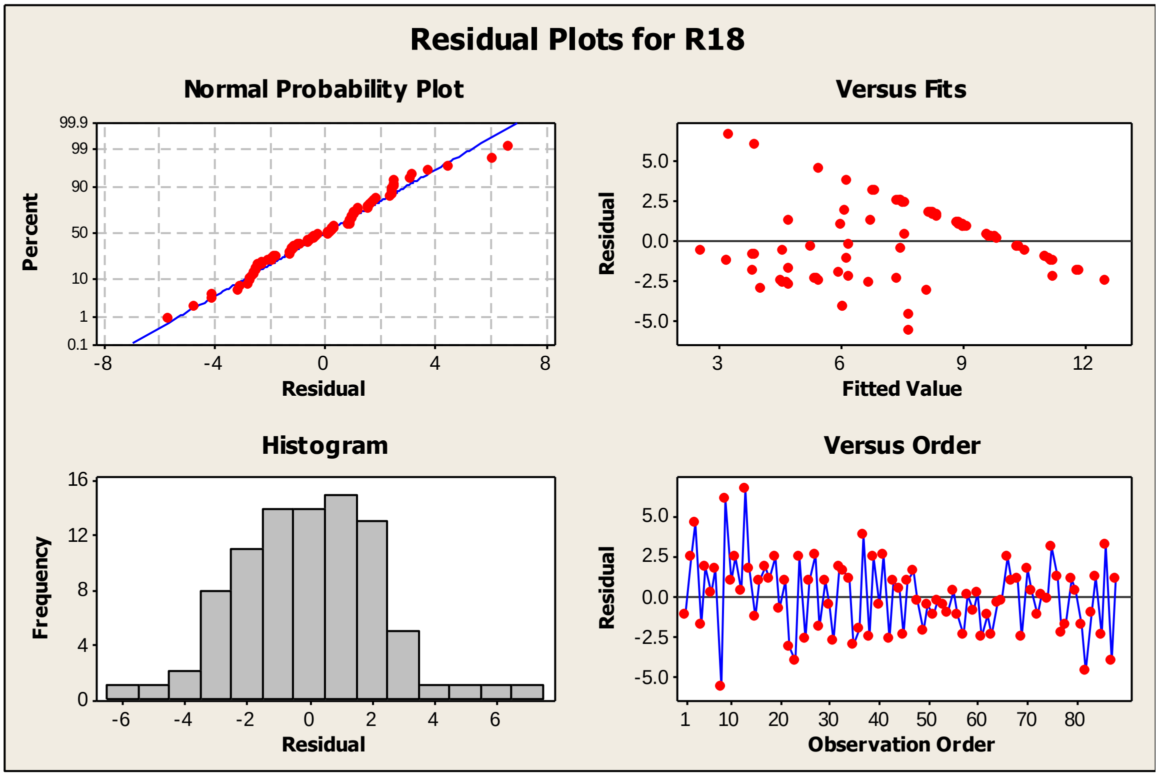

Residual Plots for R13
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order


Residual Plots for R14
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order


Residual Plots for R15
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

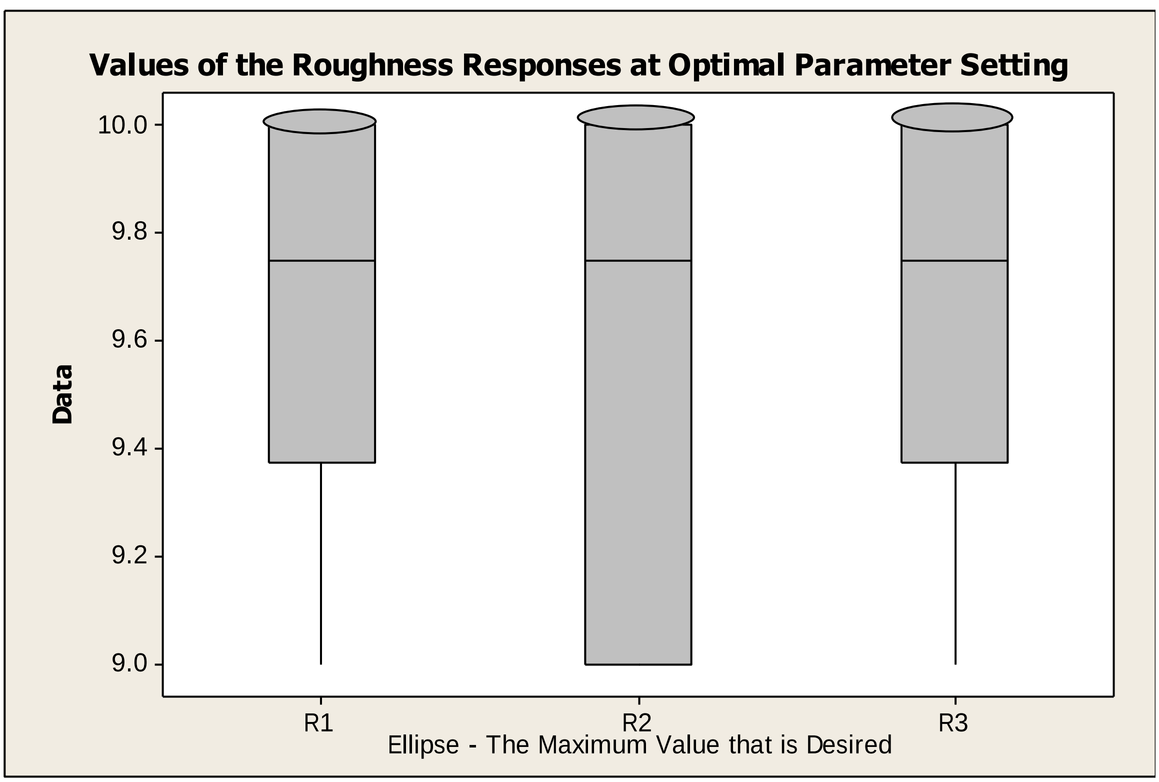

Residual Plots for R16
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

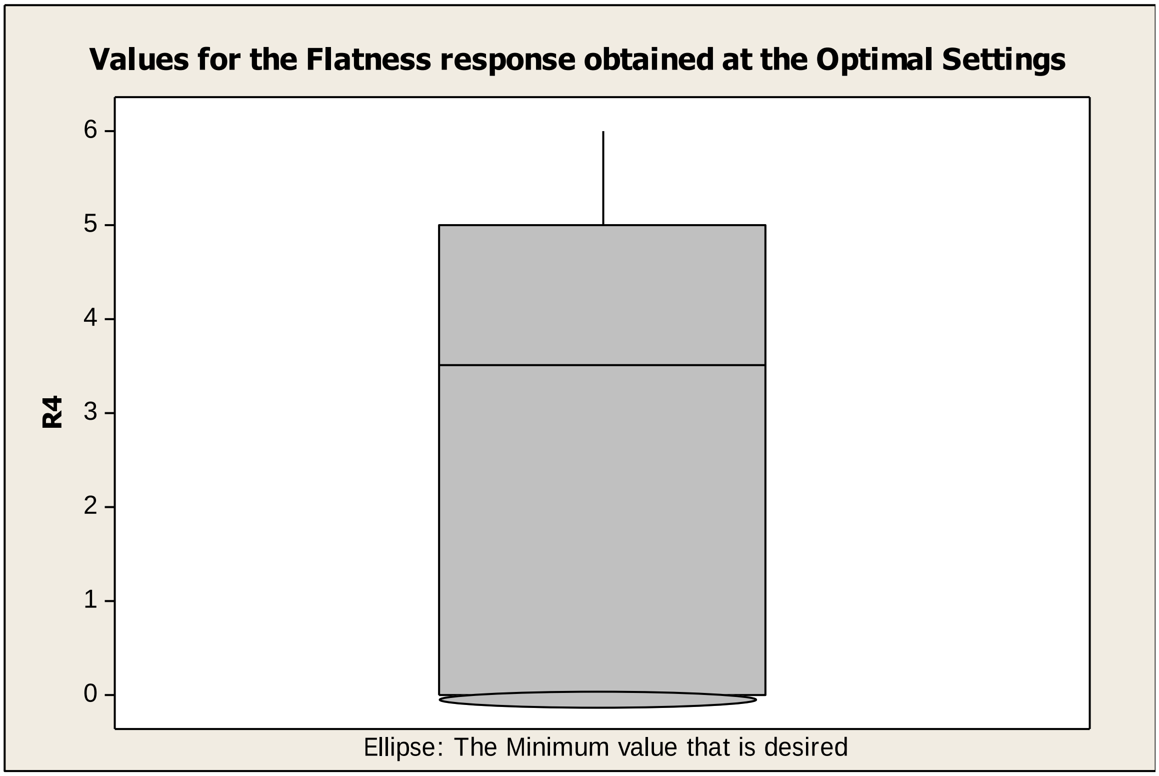

Residual Plots for R17
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

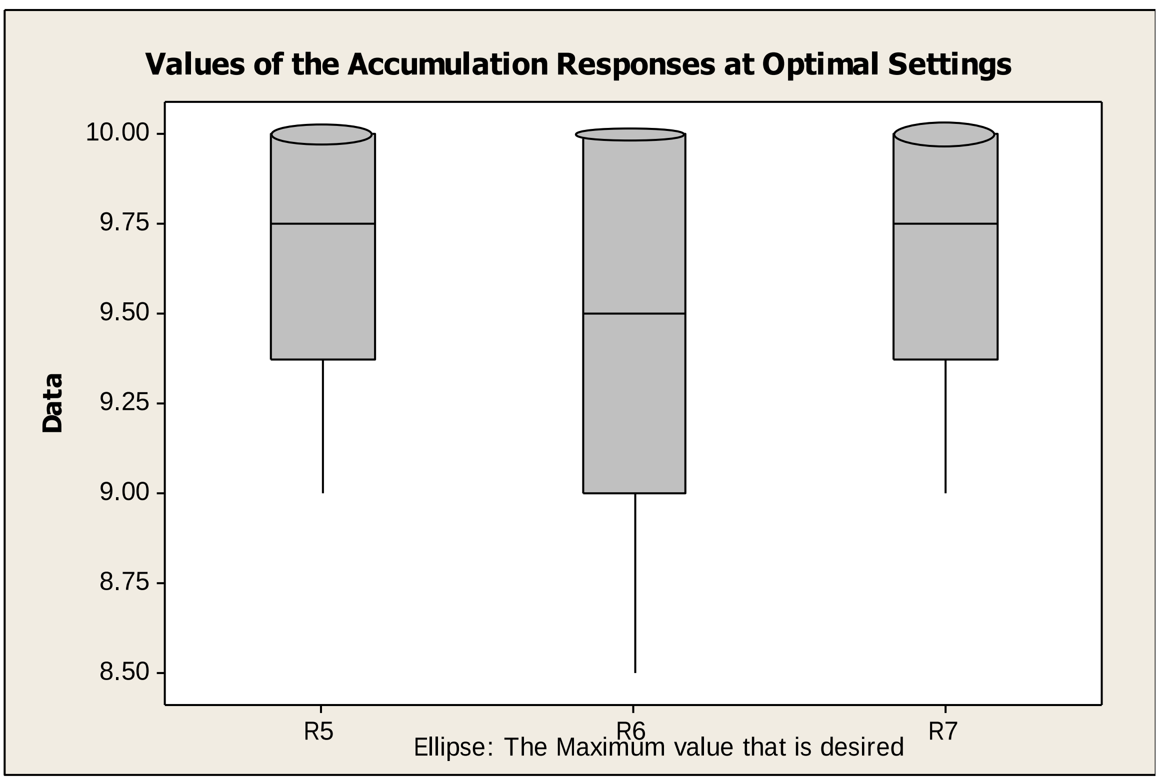


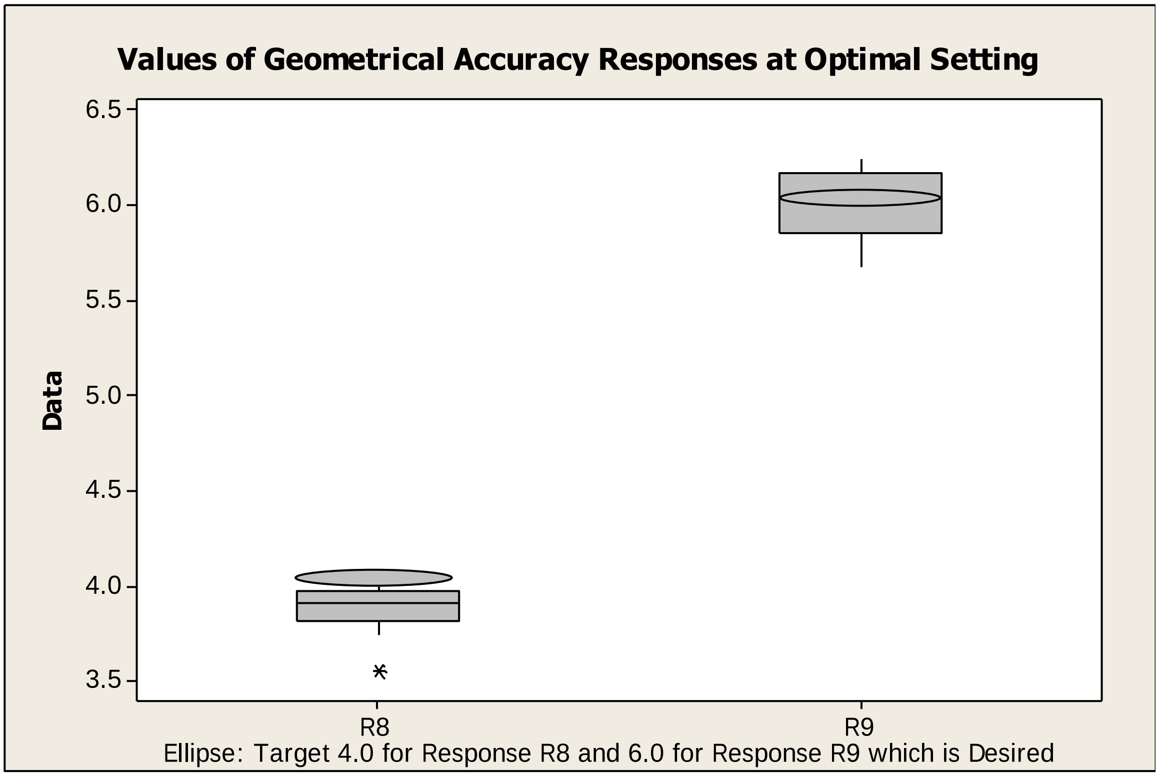
Appendix E

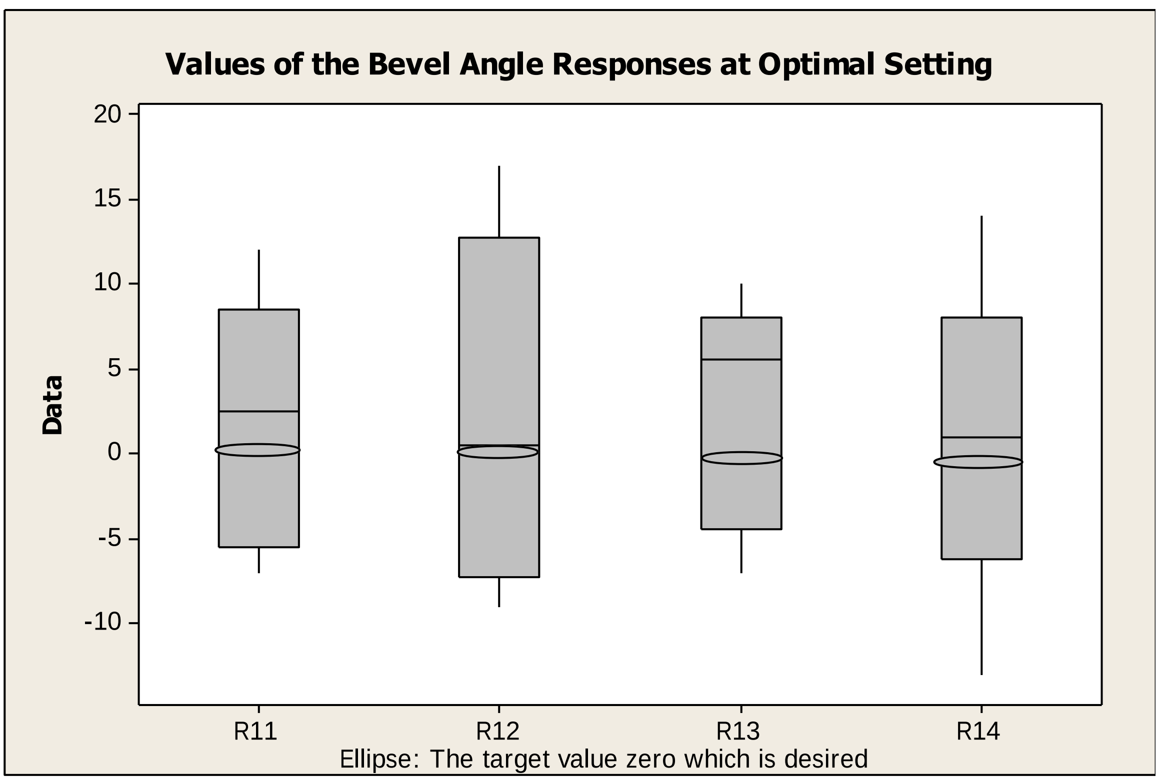
Boxplots

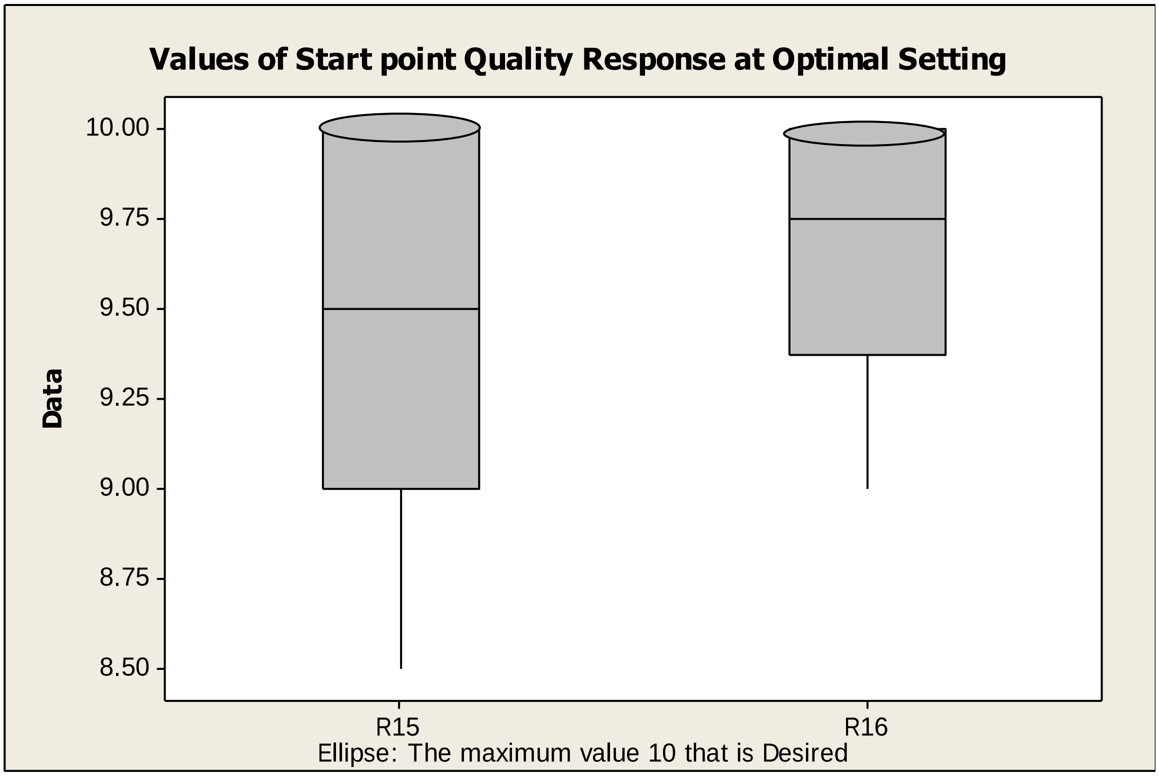


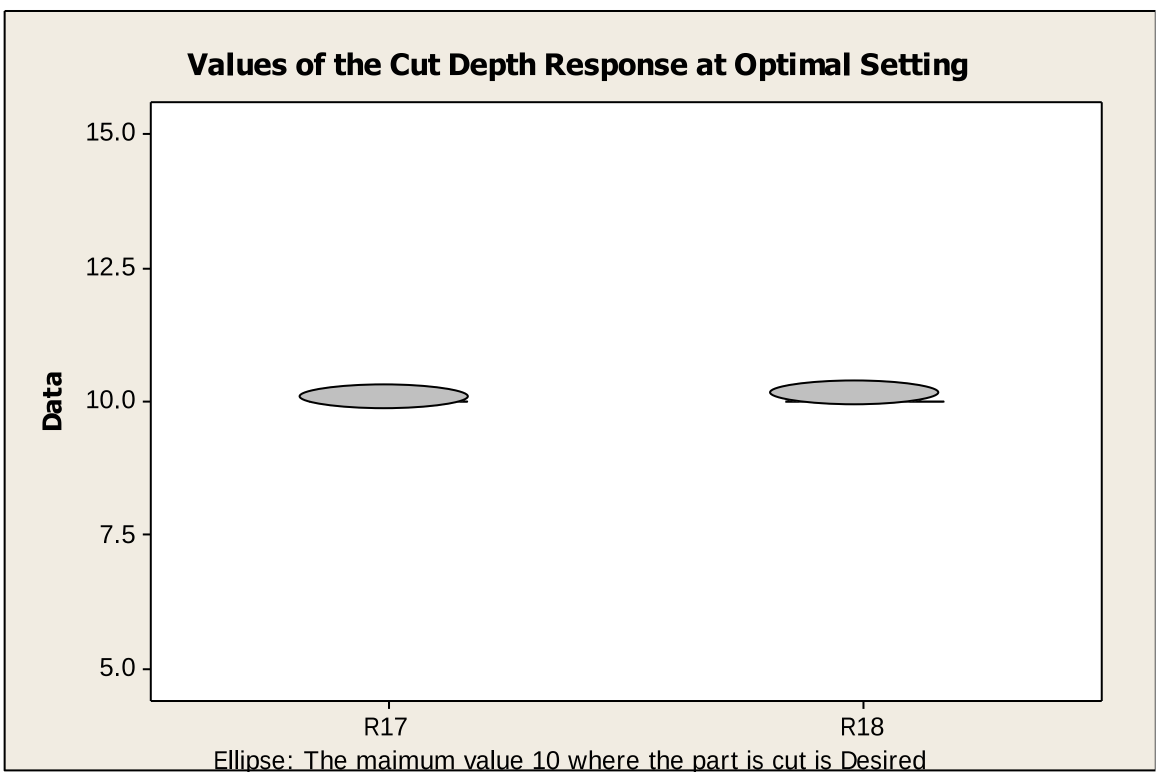

Values for the Flatness response obtained at the Optimal Settings
R4
0
1
2
3
4
5
6
Ellipse: The Minimum value that is desired


Values of the Accumulation Responses at Optimal Settings
Data
8.50
8.75
9.00
9.25
9.50
9.75
10.00
R5
R6
R7
Ellipse: The Maximum value that is desired


Values of Geometrical Accuracy Responses at Optimal Setting
Data
6.5
6.0
5.5
5.0
4.5
4.0
3.5
R8
R9
Ellipse: Target 4.0 for Response R8 and 6.0 for Response R9 which is Desired


Values of the Bevel Angle Responses at Optimal Setting
Data
20
15
10
5
0
-5
-10
R11
R12
R13
R14
Ellipse: The target value zero which is desired


Values of Start point Quality Response at Optimal Setting
Data
10.00
9.75
9.50
9.25
9.00
8.75
8.50
R15
R16
Ellipse: The maximum value 10 that is Desired


Values of the Cut Depth Response at Optimal Setting
Data
15.0
12.5
10.0
7.5
5.0
R17
R18
Ellipse: The maimum value 10 where the part is cut is Desired

VITA

Durga Tejaswani Vejandla was born in Hyderabad, India on October 21, 1985, the daughter of Hari Prasad Rao and Vijaya Kumari. She graduated from the Andhra University in 2007 in India. In August 2007, she joined M.S.T program in Industrial Technology at Texas State University-San Marcos.

Permanent Address tejaswani.vejandla@gmail.com

This thesis was typed by Durga Tejaswani Vejandla