

Optimization of SLS Process Parameters using D-Optimality

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Solid Freeform Fabrication (SFF) refers to a group of processes that manufacture parts of arbitrarily complex geometry without tooling. Currently, the operation of most SFF machines requires skilled operators with expertise in choosing process parameters in order to achieve the desired part quality. Thus, the “push-button 3D hardcopy” promise of SFF has yet to be realized. This paper presents a framework for selecting optimal process parameter values automatically for the selective laser sintering (SLS) process. The research described considered five process parameters that are important for the SLS process. To achieve quality measures from the five process parameters, optimization is inevitable. The method optimizes these process parameters of SLS with respect to a set of desired quality measures, based on user input of the relative importance of each of the quality measures. The basis for the framework is the so-called D-optimality criterion applied to a series of factorial experiments that capture empirically the relationships between the process parameters and part quality measures. The framework is implemented in MINITAB™ and a macro is used to perform the optimization

1 INTRODUCTION

Manufacturing processes that build parts by adding material on a layer-by-layer basis, in contrast to conventional methods that remove, reshape or add material are defined as Solid Freeform Fabrication (SFF) [1]. With such techniques, a prototype part is manufactured directly from a three-dimensional (3-D) CAD drawing source. Productivity in manufacturing is achieved by guiding a product from concept to market quickly and inexpensively. SFF technology aids this process as it automates the fabrication of a prototype part from a three-dimensional CAD drawing. This physical model conveys more complete information about the product earlier in the development cycle. The turnaround time for a typical rapid prototype part is a few days [1]. Conventional prototyping may take months, depending on the method used [2]. SFF is a quicker, more cost-effective means of building prototypes as opposed to conventional methods. The advent of SFF has changed mechanical design significantly [2].

While the technology involved in physically building a prototype is progressing, the process of reliably moving from a computer-generated model directly to a viable part is still in its infancy. Relatively little effort has been made to fully characterize the relationships between process parameters and part quality metrics [4]. A small percentage of users are aware of how these processes actually work, what types of results they will produce, and thus what process parameter choices will result in parts of the desired quality. This situation causes machine operators to make assumptions during the manufacturing stage as to what the designers' intentions are for the parts to be produced, and to select process parameter values accordingly. The research reported in this paper lays the groundwork for reaching the ultimate goal of “point

and click” SFF. We present an approach that allows the designer or the SFF part user to rank the final part quality measures that are important so that process parameters can be set accordingly. In particular, we describe an optimization technique for allowing the designer to know at the design stage whether a part manufactured by the given process parameters (i.e. the machine settings) can produce a part with the required quality.

1.1 Research Objectives

In all but the simplest design problems, engineers and manufacturers make decisions to optimize multiple criteria or objectives simultaneously. The problem at hand is an example of multicriteria optimization.

The purpose of this research is to develop a method to optimize the capabilities of a SFF machine so that, given particular part quality (output) measures and their relative importance, the optimal values of the process parameters (input) can be determined.

Our approach to realizing this goal involved two main objectives. First, we conducted a series of experiments to characterize the SFF process. These were factorial experiments in which several process parameters were varied systematically, and the resulting part properties were measured. The second objective was developing a computer environment for optimizing the process parameters for a target part quality. Different multicriteria optimization techniques were reviewed and the so-called D-optimality technique was chosen. The chosen implementation environment for the optimization is a commercially available statistical analysis system, MINITAB™. A demonstration program was developed in the macro programming environment of MINITAB™. The implementation was then tested and evaluated. In the next section, our experimental results are summarized. Section 3 describes the optimization macro that was developed, and section 4 presents an example of its use. We summarize the research in section 5.

2 EXPERIMENTS

A concrete set of manufacturing rules and constraints for a Solid Freeform Fabrication process allows part manufacturers to account for the designer’s intent as the part is produced. The designer can also determine if it is possible to manufacture the part satisfactorily. With information on the capabilities of a particular SFF machine, the part model can be altered as it is designed so that it will ultimately be feasible using SFF to fabricate a part with the desired quality. We have developed a standard procedure for evaluating a SFF process [4] and have applied the procedure to a SLS SinterStation 125. This section summarizes that work.

2.1 Selective Laser Sintering

Selective laser sintering is a layered manufacturing process in which powdered material is melted by laser heat into the desired shape through the repeated scanning of cross-sectional areas that will eventually form the 3D model (See Figure 1). The machine consists of two¹ pistons

¹ The most recent commercial systems have three cylinders, including two supply cylinders. The Sinterstation used for these experiments has only one supply cylinder.

within cylinders that contain, respectively, supply powder and the part being built, a roller to spread the powder evenly, radiant heaters, sensors and a controller to heat the powder, and a laser and its optics. An inert atmosphere is maintained inside the build chamber.

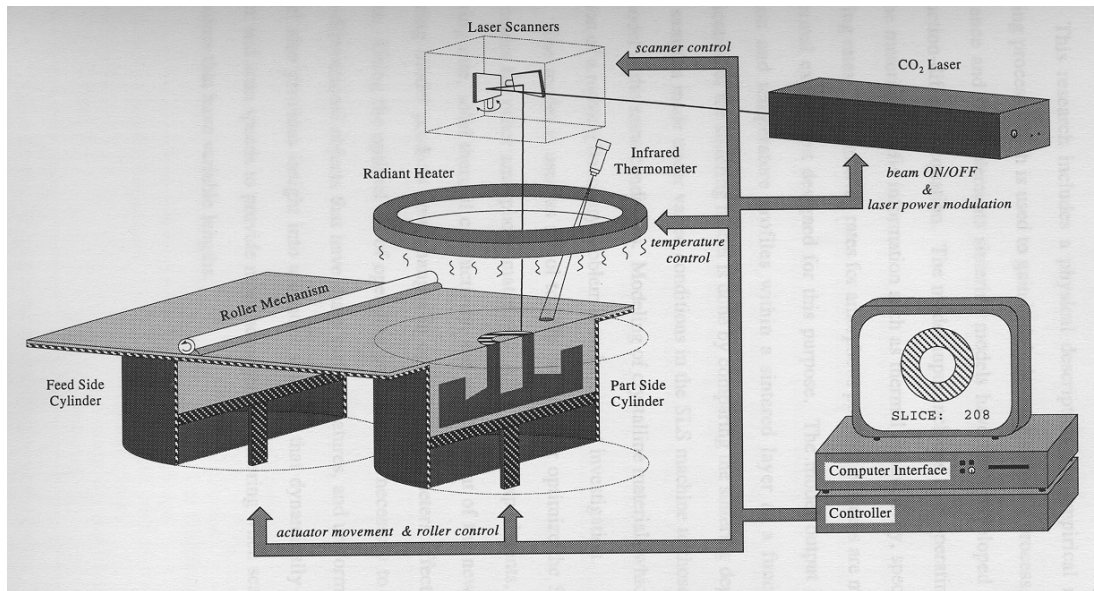


Figure 1. The selective laser sintering process [2].

The selective melting process is accomplished by a CO₂ laser. The path of the laser is controlled by galvanometers that are connected to the control computer. The computer has a sliced 3D model that dictates the path the laser takes. Various scanning techniques are used or under research [4, 5]. We used the simple X vector raster scan for our experiments.

Once the entire layer is scanned, a new layer of powder is deposited upon the previous layer. The part bed cylinder is lowered, causing the surface of the part bed to drop a prescribed amount. The powder bed cylinder is raised to provide powder for the next layer. The roller apparatus then traverses across the top of the powder bed, pushing the raised portion of the powder across the chamber to the lowered surface of the part bed. The powder covers the previously scanned areas with a thickness of powder that is determined by the amount the part cylinder has dropped. This value is the “layer thickness”. The laser then scans the next layer. This process repeats until the 3D part is completed.

2.2 Process Parameters and Part Quality Attributes

In this research, the relationships between SLS process parameters and part quality attributes were determined experimentally. Full factorial experiments were used for data collection [4]. This type of experiment allows the minimal number of builds while still providing enough information to evaluate the main effects of each input parameter, as well as the interaction effects of the combined input parameters, with the same level of precision as “one-at-a-time” experiments [6]. In full factorial experiments, an experimental run is performed for every combination of factor levels. This is the most conservative of the experiment designs.

In these experiments, only one material, Duraform™, was explored. Duraform™ is a polyamide material used for fabricating functional prototypes. The process parameters below were identified as having significant relationships to part quality.

- **Laser power.** Laser energy density, quantified by the Andrew number [3], is a function of the laser power, scan speed, and scan spacing, and has the units of J/in². For our experiments, the scan speed and scan spacing were held constant. Thus, energy density was modified by varying the laser power between 4W and 8W.
- **Powder age.** In the experiments described here, both recycled and virgin Duraform™ powders were used. Recycled powder refers to unsintered powder from previous builds. The effects of powder age were tested using virgin powder and powder that had been recycled at least 10 times.
- **Layer thickness.** Material choice severely constrains the allowable variation in this parameter. Bounding limits for layer thickness were determined from the size of the particles and the maximum layer thickness at which inter-layer bonding occurs, based on preliminary tests.
- **Part orientation.** This parameter measures the deviation between a part-based coordinate system and the build direction in the machine. The parts were oriented in the build cylinder such that the effects of scanning perpendicular to the long axis of the test part, as well as along its long axis, were tested. Additionally, orientations of 0°, 45°, and 90° around the parts' long axes were evaluated.
- **Scan vector length.** This parameter is related to part orientation in the build plane. The SLS workstation used for the experiments scans in a raster pattern. A long slender part will be scanned differently, depending on the orientation of its long axis with respect to the scanning direction.

A series of specimens was fabricated on a DTM Corp. SinterStation 125, with the process parameters described above varied according to a full factorial design. The levels of the various process parameters are summarized in Table 1 below. The effects of part orientation and scan vector length were tested by fabricating multiple parts in the same build with different orientations (both in the build plane and with respect to the build direction).

Table 1. Process parameter levels.

Parameter	No. of Levels	Levels (Uncoded)
Laser Power	2	5 W and 6.5W
Age of powder	2	Old and new
Layer Thickness	2	0.004" and 0.005"
Scan Vector Length	2	Short and long
Orientation	4	-90, 0, 45 and 90 Deg

After fabricating the specimens, we measured the following part quality attributes:

- **Part strength.** Several different measures of strength were tested using the tensile,

compressive, and bending forms of loading, and the impact strength or toughness of the sample. The values were obtained using a MTS tensometer and Izod impact tester designed for plastics. Sample hardness was measured using a Rockwell Hardness tester.

- **Dimensional accuracy.** For functional prototypes dimensional accuracy is important. Dimensional accuracy includes large dimension accuracy, small dimension accuracy and minimum positive and negative feature sizes. The analysis for each was performed at different orientations since the accuracy in the z direction is different from accuracy in the x and y directions.
- **Thermal expansion.** This attribute was measured with a Perkin-Elmer 7 series Thermal Analysis System.
- **Surface roughness.** The surface roughness was measured with a contact profilometer to evaluate the effects the parameters have on surfaces that are parallel, perpendicular, and angled with respect to the build plane.

Table 2 below summarizes the measured part attributes.

Table 2. Property limits of DuraForm™ parts on the SS125.

Property	Upper Limit	Lower Limit
Tensile Strength [psi]	7922	7
Bending Strength [psi]	10657	35
Compressive Strength [psi]	17510	1303
Density [gm/cm ³]	94.15	64.19
Impact Toughness [J/cm]	153.42	17.07
% Dimensional Error		0.72
Thermal Expansion Coefficient [1/°C]	1.69E-04	9.71E-05
Surface Roughness [μm]	33.5	7.7

3 OPTIMIZATION OF PROCESS PARAMETERS

In this section we describe our process parameter optimization tool. We chose to implement the optimization tool in an existing statistical analysis package after careful consideration of the desired functionality [12]. In particular we wanted an optimization method that would:

- Optimize the experimental design (combination of process parameter values) used to achieve the desired part quality measures.
- Use non-linear regression techniques to locate the optimal points.
- Obtain the output for the process parameters in coded/uncoded units. Coded means the values are normalized in the range of -1 to 1 , while uncoded means the values are obtained in the actual parameter units.

- Associate importances and weights with part quality measures to reflect the designer's preferences.
- Find an optimal way to balance the customer needs (many part quality measures) that a designer must take into account before reaching a conclusion about the input parameters (process parameters) for the part.
- Provide a user interface that shows the initial condition and the optimized condition and be able to switch back and forth between them.
- Illustrate the interactions among various process parameters.

Clearly, these functional requirements call for a multicriteria optimization method that uses regression (non-linear) techniques to achieve global optimization. After studying several techniques [7], the so-called "D-optimality" technique (discussed in the next section) was selected. The MINITAB™ statistical package was chosen as the implementation environment, as it supports regression analysis and provides a macro programming facility for customizing the package. Also, the graphical interface generates plots and provides a dialog capability for user input. MINITAB™, being a statistics software package, also runs factorial designs and provides response surface analysis.

3.1 D-Optimality

Since the 1980's much work has been done in the field of experimental design, and considerable attention has been given to the use of the computer for constructing experimental designs for the user [8]. For a given computer design where the response variable, y , is a function of the design variables, \mathbf{x} , we usually do not know the nature of the functional relationship. We approximate the unknown relationship or function with an empirical model of the form [8]:

$$y = g(\mathbf{x}, \mathbf{B}) + \varepsilon, \quad (1)$$

Where $g(\mathbf{x}, \mathbf{B})$ is an interpolating function, \mathbf{B} is a vector of unknown coefficients in g , and ε is the random error (or bias from true physical relationships). For factorial experiments we usually assume that the interpolating function is a low order (*e.g.*, linear) polynomial:

$$y = \mathbf{f}^T(\mathbf{x})\mathbf{B} + \varepsilon = \beta_1 f_1(\mathbf{x}) + \beta_2 f_2(\mathbf{x}) + \dots + \beta_n f_n(\mathbf{x}) + \varepsilon \quad (2)$$

Equation 2 is called the regression equation. Each of the terms $f_i(\mathbf{x})$ is a multiplicative combination of the design variables, raised to the appropriate power, that contribute to that term. For instance, for a linear model with two variables, there are four terms:

$$\begin{aligned} f_1(\mathbf{x}) &= 1 \\ f_2(\mathbf{x}) &= x_1 \\ f_3(\mathbf{x}) &= x_2 \\ f_4(\mathbf{x}) &= x_1 x_2 \end{aligned}$$

To define the interpolating function g , we need to find values for the coefficients \mathbf{B} in equation (2). We can do this by rewriting equation (2) in terms of the known response values measured from the experiments. The n sample experiments are characterized by the design points $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n$. Each design point \mathbf{x}_i consists of a unique set of values for the k design variables. Let

$$\mathbf{y} = [y_1, y_2, \dots, y_n]^T$$

be the measured response values for the n sample experiments, and

$$\mathbf{X} = [\mathbf{f}(\mathbf{x}_1), \mathbf{f}(\mathbf{x}_2), \dots, \mathbf{f}(\mathbf{x}_n)]^T$$

be the $n \times k$ design matrix. Then equation (2) can be rewritten as the set of equations:

$$\mathbf{y} = \mathbf{X}\mathbf{B} + \mathbf{e} \quad (3)$$

where \mathbf{e} is now a vector of error terms, one for each of the n sample experiments.

Unbiased estimates of \mathbf{B} can be found if the expected error values are zero and the variances of the errors for all design points are the same:

$$\begin{aligned} E(\mathbf{e}) &= \mathbf{0} \\ V(\mathbf{e}) &= \sigma^2 \mathbf{I} \end{aligned} \quad (4)$$

where s is the standard deviation and \mathbf{I} is the identity matrix.

With equation (3), the least squares technique can be used to compute $\hat{\mathbf{B}}$, an estimate of \mathbf{B} , assuming the number of design points in the experiment exceeds the number of parameters β_i :

$$\hat{\mathbf{B}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \quad (5)$$

Using these estimates and equation (2), the estimate the value of the response variable is:

$$\hat{y} = \mathbf{f}^T(\mathbf{x}) \hat{\mathbf{B}} \quad (6)$$

A measure of the accuracy of the estimates $\hat{\mathbf{B}}$ is the variance-covariance matrix $V(\hat{\mathbf{B}})$, defined as:

$$V(\hat{\mathbf{B}}) = \sigma^2 (\mathbf{X}^T \mathbf{X})^{-1} \quad (7)$$

The optimal design is one that minimizes the variance defined in equation (7). However, the minimum of a matrix is not a well-defined concept. A number of operational criteria have been developed. One criterion, D-optimality, seeks to minimize the determinant of the matrix $(\mathbf{X}^T \mathbf{X})^{-1}$. Of the available optimality criteria, D-optimality gives accurate parameter estimates

and takes the least time to compute [8, 9, and 10]. D-optimality is also appropriate when multiple responses are involved. Hence we have chosen the D-optimality criterion for our research.

3.2 Implementation

In this research, D optimality is applied to the 9 responses (part quality measures), the data for which was obtained from [4]. The implementation uses a D-optimality macro in MINITAB™. For each optimization run, the part quality measures to be optimized are first chosen. Then the goal for each response (maximize, minimize, or target) is chosen, and the user provides values for parameters (limits and targets) appropriate for each type of goal. Weights are then associated with the responses. The weights define the shape of the desirability function. The values of the weights vary from 0.1 to 10 to de-emphasize or emphasize the response. Finally, importances are assigned to the responses. Values of importance must be between 0.1 and 10 [11]. If all responses are equally important, the default value of one is used for each response. The composite desirability is then the geometric mean of the individual desirability [11]. However, if some responses are more important than others, the user can incorporate this information into the optimal solution by setting unequal importance values.

4 EXAMPLE: PROSTHESIS SOCKET OPTIMIZATION

In this section we present an example where different target values for the part quality measures are required for different regions of the part. The example focuses on determining the optimal process parameters for fabricating a patella tendon bearing (PTB) socket, part of prosthesis used by below-the-knee amputees. An image of a PTB socket is shown in Figure 2. This socket is designed such that the residual limb contacts all areas of the socket. However, the socket is designed with compliant areas in the regions where pressure sensitive tissue touches the socket. The patella tendon area is the weight bearing part in the socket while the pressure sensitive areas are the distal end and the fibula end (see Figure2). The bottom of the socket consists of a pylon fitting that is attached to an aluminum pylon and prosthetic foot assembly.

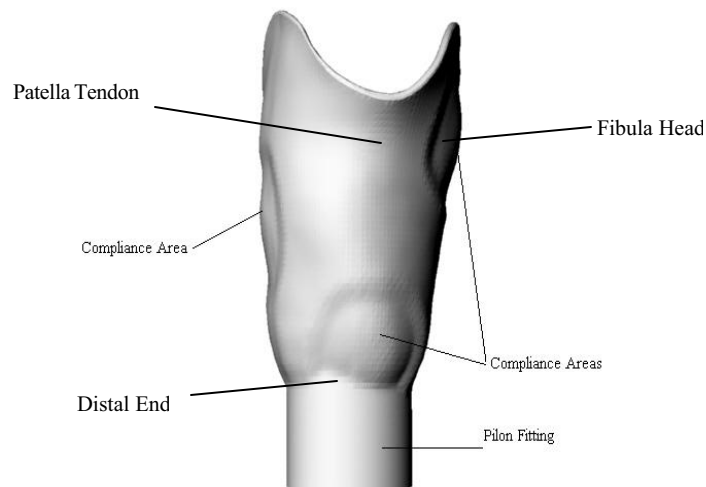


Figure 2. Patella tendon bearing socket.

For this example the compliant areas have different part quality targets than the other areas of the socket. The two part quality measures identified as the most important for the user in each area are tensile strength and 3 point bending strength, respectively. Goals, weights and importances were assigned to each of the nine quality measures and optimized. The macro begins by assuming a full factorial design and obtains data from the “responses.xls” file. The macro then performs sequential optimization, and the search improvement for optimization is done using one exchange point. The following were the goals, importances and weights for the compliant part of the socket.

Table 2. Properties of the compliant part of socket

Quality Measures	Goal	Lower	Target	Upper	Weight	Importance
Tensile	Maximum	19	7775	7775	1	1
3 Point	Minimum	29	1000	11090	1	10
Charpy	Maximum	17.95	153.4	153.4	1	8
Density	Target	64.19	94.2	94.2	1	6
Compress	Maximum	1302.5	16665.1	16665.1	1	0.5
Surface Roughness	Target	7.7	7.7	33.5	1	2
Thermal Exp	Minimum	0	90E-6	133E-6	1	0.1
Dimension Ave	Minimum	0.1	0.1	1.7	1	9
% Dimension	Minimum	0.3	0.3	43.8	1	9

As can be seen from the parameter settings the goal is to minimize the 3 point bending strength, with a maximum importance. This is because the areas where the socket needs to be compliant must have little bending resistance, *i.e.*, minimum 3 point bending strength. The composite desirability achieved for the given settings (goals, weights and importances) of the process parameters is 0.52613. The parameter settings for the five process parameters (uncoded) according to this optimization are:

Table 3. Parameter settings for the five process parameters for compliant areas of socket.

Parameter	Setting
Power	5.24
Thickness	0.005
Age	new
Vector Length	long
Orientation	-90

For load-bearing areas of the socket the goals, importances and weights are summarized below in Table 4. The goals include maximizing the tensile strength, with a maximum importance attached to this goal. As these parts of the socket must bear the weight of the patient, tensile strength becomes the controlling material property. The composite desirability achieved for the given settings (goals, weights and importances) of the process parameters is 0.50847. The parameter settings for the five process parameters (coded) according to this optimization are given in Table 5.

Table 4. Properties of the remaining part of socket

Quality Measures	Goal	Lower	Target	Upper	Weight	Importance
Tensile	Maximum	19	7775	7775	1	10
3 Point	Minimum	29	1000	11090	1	4
Charpy	Maximum	17.95	153.4	153.4	1	8
Density	Target	64.19	94.2	94.2	1	6
Compress	Maximum	1302.5	16665.1	16665.1	1	6
Surface Roughness	Target	7.7	7.7	33.5	1	2
Thermal Exp	Minimum	0	90E-6	133E-6	1	0.1
Dimension Ave	Minimum	0.1	0.1	1.7	1	9
% Dimension	Minimum	0.3	0.3	43.8	1	9

Table 5. Parameter settings for load-bearing areas of socket.

Parameter	Setting
Power	5.58W
Thickness	0.0046”
Age	Old
Vector Length	Long
Orientation	-70 degree

This example focuses on a part to be manufactured by SLS in response to different customer needs for different parts of the same socket. The optimization function shows that the power, thickness and vector length will have to be changed for the socket to work as intended.

In the compliant areas of the socket the power level should be lower than that in the load-bearing areas of the socket. Layer thickness, powder age, and orientation should also vary for the compliant areas and the load-bearing areas of the socket. See Table 6 below for a comparison of the values:

Table 6. Comparison of five process parameters for compliant and the load-bearing areas of socket.

	Compliant Part	Rest of the socket
Power	5.24 W	5.58W
Thickness	0.005”	0.0046”
Age	New	Old
Scan Vector Length	Long	Long
Orientation	-90 degree	-70 degree

4.1 Interpretation of Results

In this section we interpret the results of optimizing the process parameters for the application described above, beginning with laser power. An increase in the process parameter

laser power means the powder melts more thoroughly and forms better bonds between layers. This leads to increases in tensile, 3 point bending, and compression strengths. Better bonding in turn leads to better dimensional. For the load-bearing areas of the socket the tensile strength has importance 10 (most important) followed by average dimension, % dimension error and charpy impact strength. These areas of the socket must be structurally sound, *i.e.*, the tensile strength should be large enough to transfer the patient's weight to the pylon fitting.

Increasing the layer thickness reduces the tensile, 3-point bending and compressive strengths [4]. This is because, with an increase in layer thickness for a given power, the powder does not melt as thoroughly as it would for thinner layers or higher power. For the compliant part the 3 point bending is the most important part quality measure followed by average dimension, % dimension error and charpy impact strength. Thus, a smaller 3 point bending strength is desired to allow more bending in compliant. Layer thickness affects several part quality measures, the most important being the build time. The surface roughness should decrease with decreased layer thickness because the stair step effect [4] between layers is reduced.

Powder age indicates either new powder or recycled powder. Watson [4] showed that accuracy decreases with an increase in the number of times the powder is recycled. Because compliance is increased by changing the local geometry (either thickness or by incorporating compliant features), accuracy is important in the compliant areas of the socket. Also, recycled powder requires more thermal energy, which can have the side effect of part growth or curl.

The scan vector length affects the density of the part produced. The part starts to cool immediately after the laser passes over the powder. The longer the laser takes to melt the adjacent powder the higher the thermal gradients. With long scan vectors the powder takes longer to cool than with short scan vectors [4]. Other part quality measures are also affected by the scan vector length due to the galvanometer motion. The motion of the galvanometers is such that, when the direction changes, they first decelerate, stop briefly and then accelerate in the other direction. This can result in high energy density over the scanned area. Also a part with complex geometry may require small scan vectors. Since this prosthesis does not have any complex geometric features, we decided to use large scan vector lengths. This speeds the build process up and reduces costs.

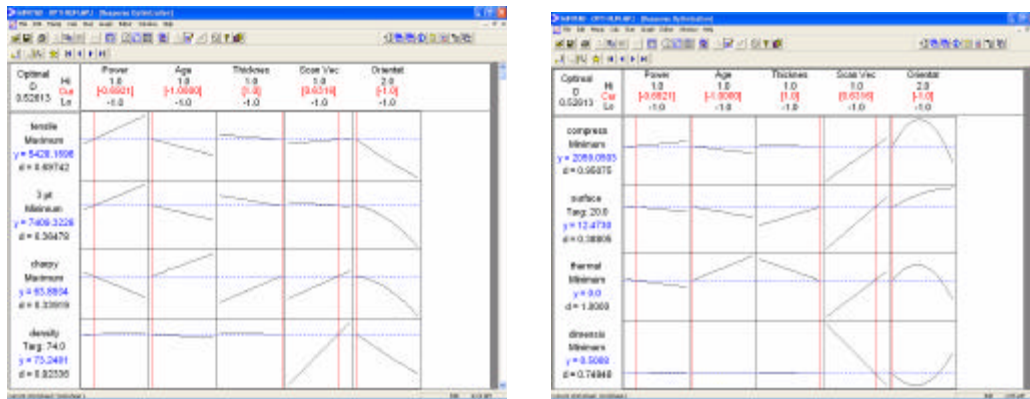
Orientation is a major factor in determining the final part quality. For taller parts, the machine processes more layers, and more time is required to complete the build. Laser scan time is dependent on volume and not on orientation. If the part can be oriented in such a way that the longest side is in the plane then the time and cost needed to produce the part are greatly reduced. Orientation also affects part strength. In the x - y direction the powder melts homogeneously, while in the z direction there is a possibility of improper bonding between layers. This can lead to relatively poor lamination and strength reduction in that direction. For compliant areas, where more strain is desired for a given stress value, Watson [4] shows that orienting the part with the longest dimension in the z direction results in more compliance and lower 3-point bending strength. Since our method does not account for the geometry and sizes of the parts in x , y and z direction we assume that the part is oriented to minimize the time of manufacture and ultimately the cost. For the prosthesis socket, this means the longest dimension is in the x - y . The parameter optimization results suggest that for the required part quality measures the orientation should be

such that the longest dimension is along the z direction for the compliant areas of the socket and slightly tilted (20 degrees to the earlier orientation) for the load-bearing areas of the socket. This, of course, is not possible, but serves to illustrate how our method accounts for orientation in process parameter selection.

4.2 Optimization Plots for Prosthetic Socket

The MINITAB™ user interface presents the optimization results in graphical form. Figures 3 and 4 show optimization plots obtained for the prosthetic socket example. There are six columns in each figure. The first column lists the parameters and gives the optimal value for the settings. The subsequent columns give the process parameters, high and low coded values, and the optimal value. For instance, the second column plots the variation of power from -1 to 1 in coded units. The vertical red line in each column shows the optimal process parameter settings for all the different part quality measures. The dotted blue line in each row gives the response for the set weights and importances.

The plots summarize the optimize results, allowing the user to effectively detect trends. For instance, in Figure 4 the tensile strength variation is linear (in blue) and hence shown by a straight line. In contrast, for the compressive strength, the variation for orientation process parameter is quadratic, indicated by the curve in the plot. A comparison of Figures 3 and 4 shows that the optimal points of operation are different (shown by red vertical lines). Also the responses for the part quality measures are different in both the figures for a given response, as the objectives, weights and importances are different in each case.



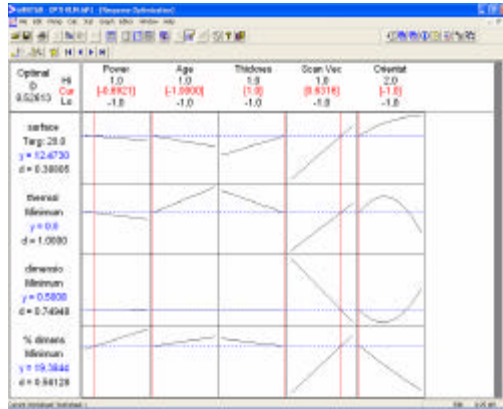


Figure 3. Optimization plots for compliant areas of the socket.

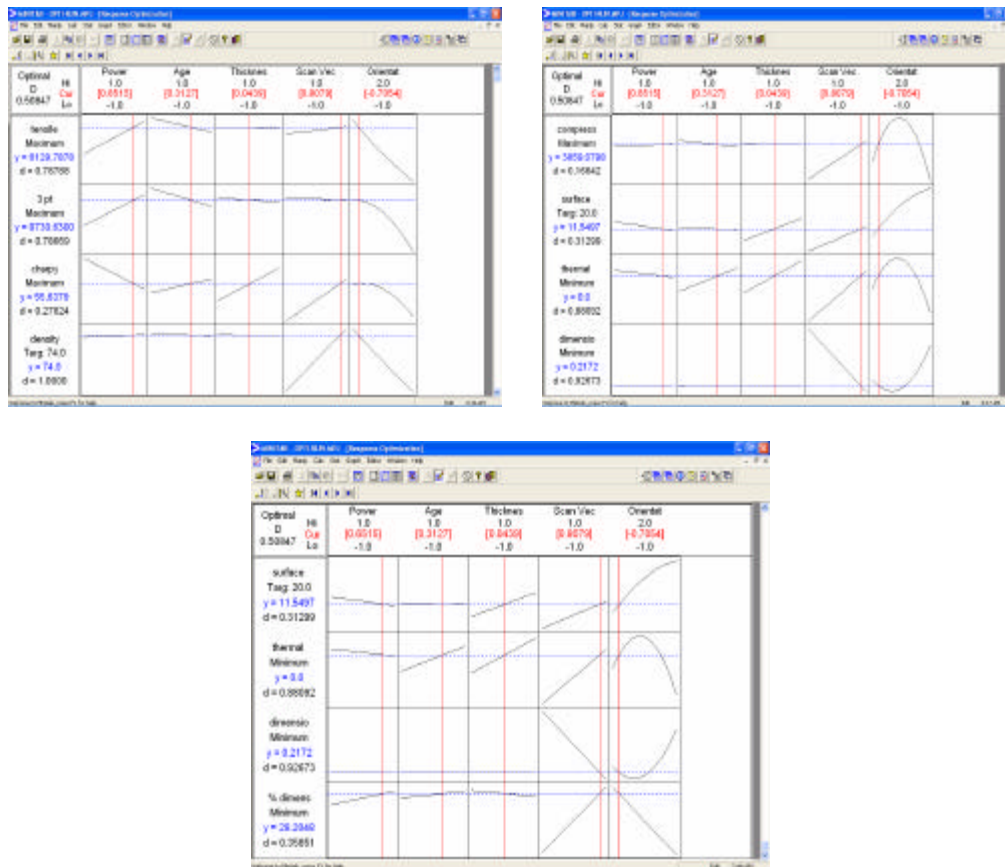


Figure 4: Optimization plot for load-bearing areas of the socket.

5 CONCLUSIONS

This paper describes a system for choosing optimal process parameter values for manufacturing a part using selective laser sintering. The system uses the D-optimality algorithm and nonlinear regression to determine the best values for process parameters based on experimental part quality data from a series of factorial experiments. Our approach allows the designer to prioritize the different part quality metrics and focus on those that are most important

to the customer. Using this system, the part designer can balance the various requirements of a customer to achieve the optimal part quality.

The research suggests several avenues of future work. The most obvious extension of the work is to apply the framework to other SFF machines and processes. Watson [4] describes a methodology for characterizing SFF processes. We believe the framework described in this paper is general enough to accommodate data from other processes and machines, but this must be shown with concrete examples

A second area of improvement is the optimization environment itself. The current implementation of the macro requires use of the MINITAB™ drop-down menus. This is a cumbersome artifact of the chosen implementation vehicle. Other implementation tools should be studied to determine if a more suitable environment is available.

A third, more general extension of this tool is extending to a true manufacturability evaluator. Currently the system only reports the optimal process parameters. It does not provide a measure of how manufacturable the design is, nor does it give suggestions on improving manufacturability. This goal is clearly necessary to realize the potential of SFF to be “push button” manufacturing technologies.

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