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EFFICIENT SAMPLING FOR DESIGN OPTIMIZATION OF AN SLS PRODUCT

Nancy Xu*, Cem C. Tutum

Department of Computer Science, University of Texas at Austin, Austin, TX 78712
* Corresponding Author E-mail: nancyxu@utexas.edu

Abstract

In this work an efficient constrained surrogate-based sampling algorithm is implemented to optimize Selective Laser Sintering (SLS) process parameters for maximizing the tensile strength of a tensile specimen. Two variations of the algorithm have been implemented and tested on a Farsoon HT251P machine using (polyamid) PA3300 polymer powder. The algorithm is based on building a statistical predictive model of the objective response (i.e., maximization of tensile strength), aggregating the constraint function (i.e., limited amount of warping), in an iterative manner by simultaneously improving the accuracy of the predictive model as well as searching for the optimum set of process parameters. The difference in two algorithmic variations is the number of samples to update at each iteration. While the first method is based on a single sample update, the latter searches for multiple simultaneous updates to let the manufacturer try several potentially good sets of parameters in the same machine to eventually speed up the experimental evaluation procedure.

Introduction

Additive manufacturing refers to a set of processes that deposit layers of material in order to form an object. One such popular technique is Selective Laser Sintering (SLS) that primarily works by depositing and melting layers of powders. Objects of great complexity can be produced from a computer aided design (CAD) file, making this very popular for their ability to quickly fabricate prototypes and parts that would be time intensive to construct using conventional methods.

The mechanical properties of printed parts are an important consideration for both prototyping and manufacturing. The part must meet certain mechanical and physical requirements for use or testing. Material properties such as particle size distribution and reflectiveness are an important consideration [1], but they are not the only factors affecting the mechanical properties of the printed part. Those properties are also dependant on process parameters such as laser power, scan spacing, and scan speed [2]. Finding the optimum process parameters that produce the highest quality parts is critical.

Mathematical modeling of the process may seem like a possible way to obtain the optimum parameters. Pharhami and McMeeking create a system of equations whose solutions predict the movement of particles during the sintering process [3]. Zhou et al. present a model that simulates the part bed upon which heat transfer analysis needs to be done [4]. While the results of these models appear to be accurate, they require significant computational time and power due to the large number of elements. Additionally, deriving the formulas is a complicated process which may not generalize well to different materials.

Singh and Prakash also create a mathematical model of the SLS process to predict density [5]. However, Singh and Prakash used a factorial design of experiments approach to collect data used to predict their equation for density. Factorial design of experiments (DOE) is an experimental method for obtaining information by combinatorially varying controllable factors. Ghanekar and Crawford. use this method to characterise the SLS process for finding the parameters that produce optimal parts [6]. However, the cost of exploring the parameter space using factorial DOE increases exponentially with the number of parameters. To address this, Singh and Parkash add an initial screening stage to reduce the number of parameters, making it a two factorial design [5]. Liu et al. explore the parameter space using Taguchi's method [7]. The number of experiments is reduced by selecting a small set from all the possible combinations of factors based on an orthogonal array. Negi et al. use a face-centered central composite design to reduce trials [8].

Because SLS parameters are actually continuous, results from a DOE process can then be fitted to a mathematical formula for better analysis and optimization. Negi et al. and Sachdeva et al. (2013) fit their results using a quadratic model [8, 9]. This allows them to discover optimums that exist between the values chosen for a DOE design. Ning et al. use the collected data to train a neural network to predict the optimum process parameters [10].

In this paper we propose a constrained efficient (single/parallel infill) sampling-based optimization algorithm to find the optimum SLS process parameters for improving the tensile strength of a tensile bar while reducing the number of physical experiments.

Methodology

Experiments were carried out on a Farsoon HT251P SLS-machine using PA3300 polymer powder (*see* Fig. 1). The laser power and scan spacing are considered to be the control (optimization) parameters. Tensile strength of the printed parts is aimed to be maximized subject to the limit based on product quality (i.e., warped tensile specimens are considered to be infeasible solutions).

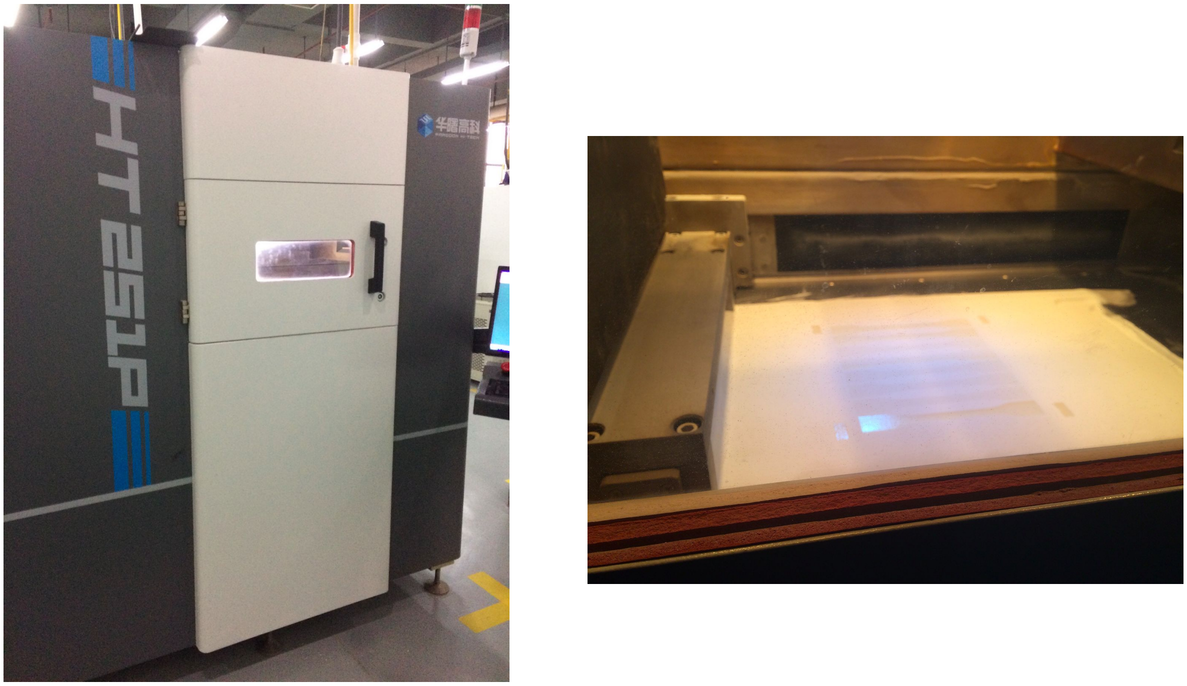


Figure 1. (Left) Farsoon HT251P SLS-machine used for the experiments. (Right) An image captured during the scanning process.

Fig. 2 shows how the width and height measurements are considered in order to evaluate the performance of each process parameter setting. Each experiment consists of six tensile test parts printed at the specified parameters. The dimensions of the part are measured before the tensile test is performed. Afterwards, the tests with the highest and lowest tensile strength are discarded. The remaining four results are then averaged to determine the final tensile strength.

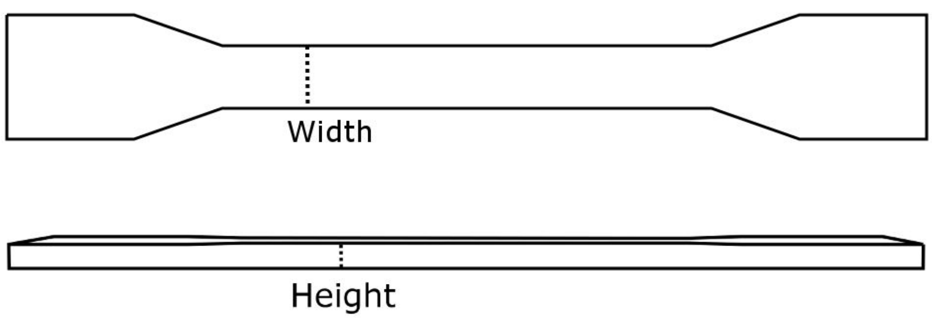


Figure 2. A tensile bar and how the width and height measurements are taken shown schematically.

The initial experiments are chosen using the optimal latin hypercube sampling (LHS), which is a uniform space filling sampling method. The same set of initial experiments was used for both methods.

Laser Power (W)	Scan Spacing (mm)	Tensile Strength (MPa)
25	0.17	44.9
53	0.3	45.3
32	0.26	27.7
46	0.21	48.5
39	0.08	NaN
60	0.12	NaN

Table 1. Initial experiments and their observed tensile strength. Results for 39W/0.08mm and 60W/0.12mm were unable to be obtained (NaN).

Experiments at 39W/0.08mm and 60W/0.12mm showed significant warping. The resulting tensile strengths are inaccurate and most of the printed parts could not be tested at all. The objective value of the tensile stress measurement is instead considered to be,

$$f = \text{Current worst tensile strength} - \text{total deformation} * 1.5 \quad (1)$$

where total deformation is the difference between the average dimensions of viable test parts from the dimensions of the warped one. We are aware of the fact that tensile strength and deformation have different units (i.e., MPa and mm, respectively), but our intention is to assign a fitness value, to an infeasible solution, lower than the current worst acceptable (not warped) solution. This approach, turning a constrained problem into an unconstrained one, will eventually guide the search towards better regions of the design space.

Overall efficient sampling framework is shown in Fig. 3. First, the optimal LHS produces the initial sample set of six tensile bars for building the first surrogate (y) of the objective function (i.e., tensile stress of the printed specimen). Each physical experiment considered to be an expensive or time consuming design evaluation, Y.

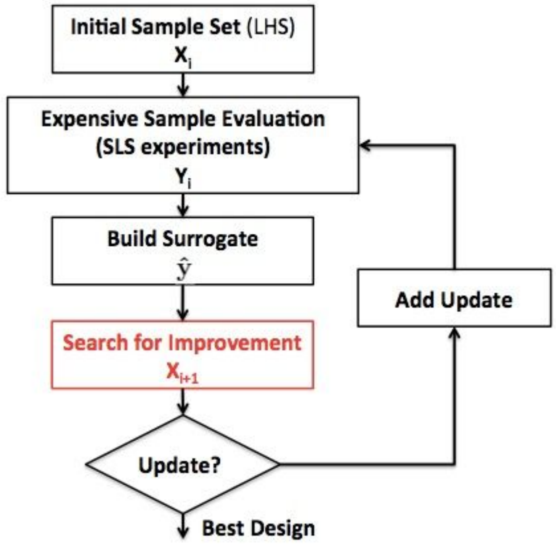


Figure 3. Surrogate based optimization framework

Due to the nonlinear correlation between various part properties and machine parameters, Gaussian Process (GP) or Kriging is chosen to construct the surrogate. In addition to being superior to a polynomial response surface model or artificial neural networks (in case of limited number of samples) for approximating complex nonlinear functions, the process of constructing a GP surrogate also provides an estimate of the mean square error (MSE). These output of the surrogate, i.e., y and MSE, are then used to calculate the expected improvement (EI) function, which is a statistical acquisition function to be maximized to find new update points to improve the fitness value upon the current best process setting found so far. The EI is given below in Eq. (2),

$$\mathrm{EI} = \begin{cases} (y_{best} - \hat{y}(x))\phi(\frac{y_{best}-\hat{y}(x)}{s(x)}) + s(x)\varphi(\frac{y_{best}-\hat{y}(x)}{s(x)}), & \text{if } s > 0 \\ 0, & \text{if } s = 0 \end{cases} \tag{2}$$

where Φ and φ are the cumulative distribution function and probability density function of a normal distribution, respectively, s(x) is the MSE estimate at new candidate sample vector x, and y_{best} is the best observed value so far. The maximum of the EI surface is sought using a genetic algorithm. In this paper we investigated using a singular infill method and a parallel infill variation. More details about the computation of EI can be found in [11]. This methodology was previously applied in pultrusion and friction stir welding processes [13, 14], respectively. Next two subsection give more details about the update strategy, i.e. the number of sample points (optimal candidates).

1. Singular Infill

The first method will return a single infill point per iteration of the algorithm. The fitness of a point is defined as its EI value.

2. Parallel Infill

The second method returns *k* infill points per iteration, where *k* is defined by the user. To prevent the infill points from being clustered tightly around one optimum, a points fitness is modified depending on the closeness of its neighbors. We use a shared fitness formulation, Eq. (3), proposed by Goldberg [12],

$$f'(i) = \frac{f(i)}{\sum_{j=0}^{n} sh(i,j)}$$
$$\text{sh(i,j)} = \begin{cases} 1 - \left(\frac{d(i,j)}{\sigma_{share}}\right)^{\alpha}, & \text{if } d < \sigma_{share} \\ 0, & otherwise \end{cases} \tag{3}$$

where d(i, j) is the distance between points *i* and *j* and σ_{share} is a predetermined value controlling the diversity or the number of niches. If the distance between two points is greater than σ_{share}, then they will not affect each other's fitness value. The fitness value, *f'*, of the samples locating in more crowded regions will be lower than their original fitness value (*f*). This will automatically let the algorithm locate a number of diverse and optimal solutions in a single optimization run.

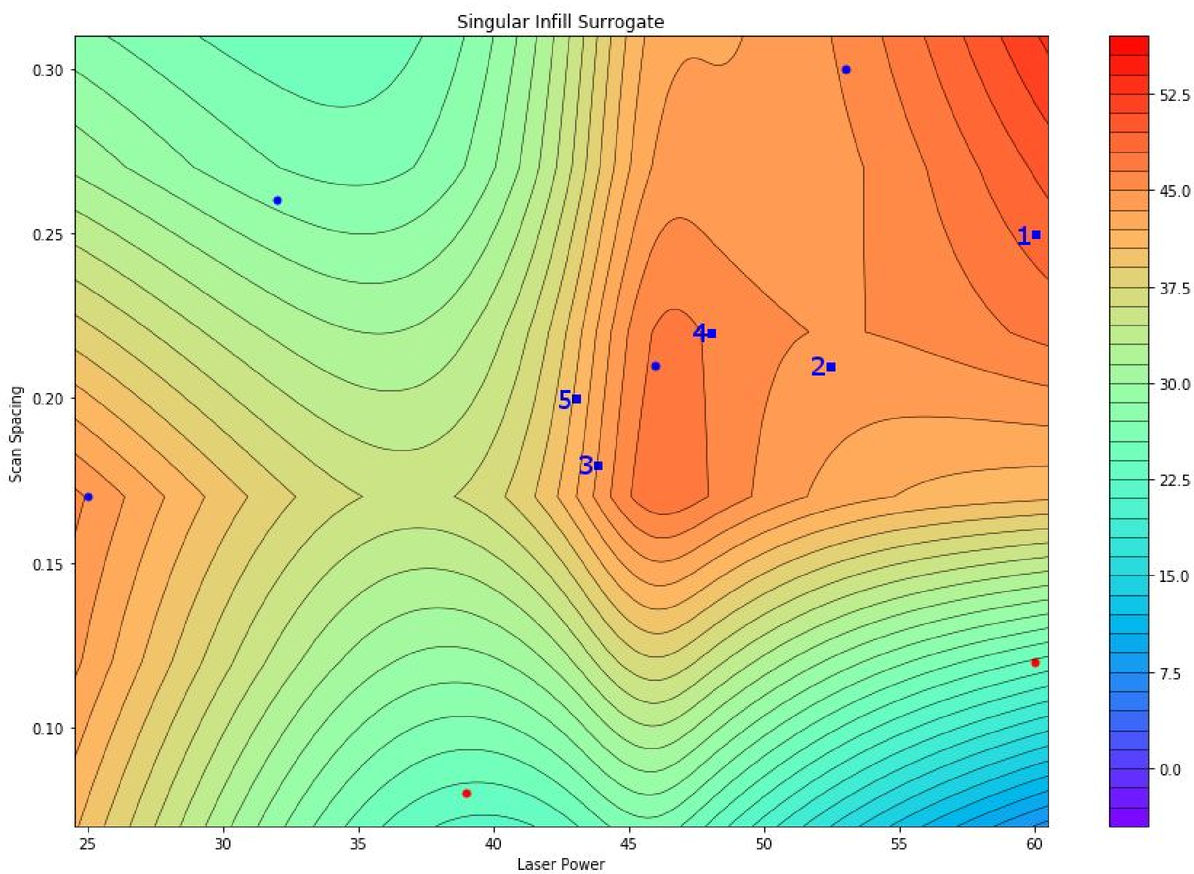
However, clustering is possible even after the transformation. To address this, the genetic algorithm is modified to account for distance between optima. In order to be considered to be part of the top *k* set of infill points, a point must have a better fitness than at least one member of the set and also be at least a certain distance apart from every member of the set.

Results

The first set of tests used the singular infill method. Five infills were tested with one new sample gained per day.

Infill #	Laser Power (W)	Scan Spacing (mm)	Tensile Strength (MPa)
1	60.0	0.25	47.9
2	52.4	0.21	46.3
3	43.8	0.18	44.3
4	48.0	0.22	46.3
5	43.0	0.2	42.1

Table 2. Singular Infill Results



●-Feasible Initial Experiment ●-Infeasible Initial Experiment ■-Infill Point

Figure 4. Surrogate constructed after five infill points.

The singular infill algorithm searches the space around the initial experiment with the highest tensile value. Low experimental results around that point has led to a high fitness estimate in the top right corner (i.e, high power and scan spacing).

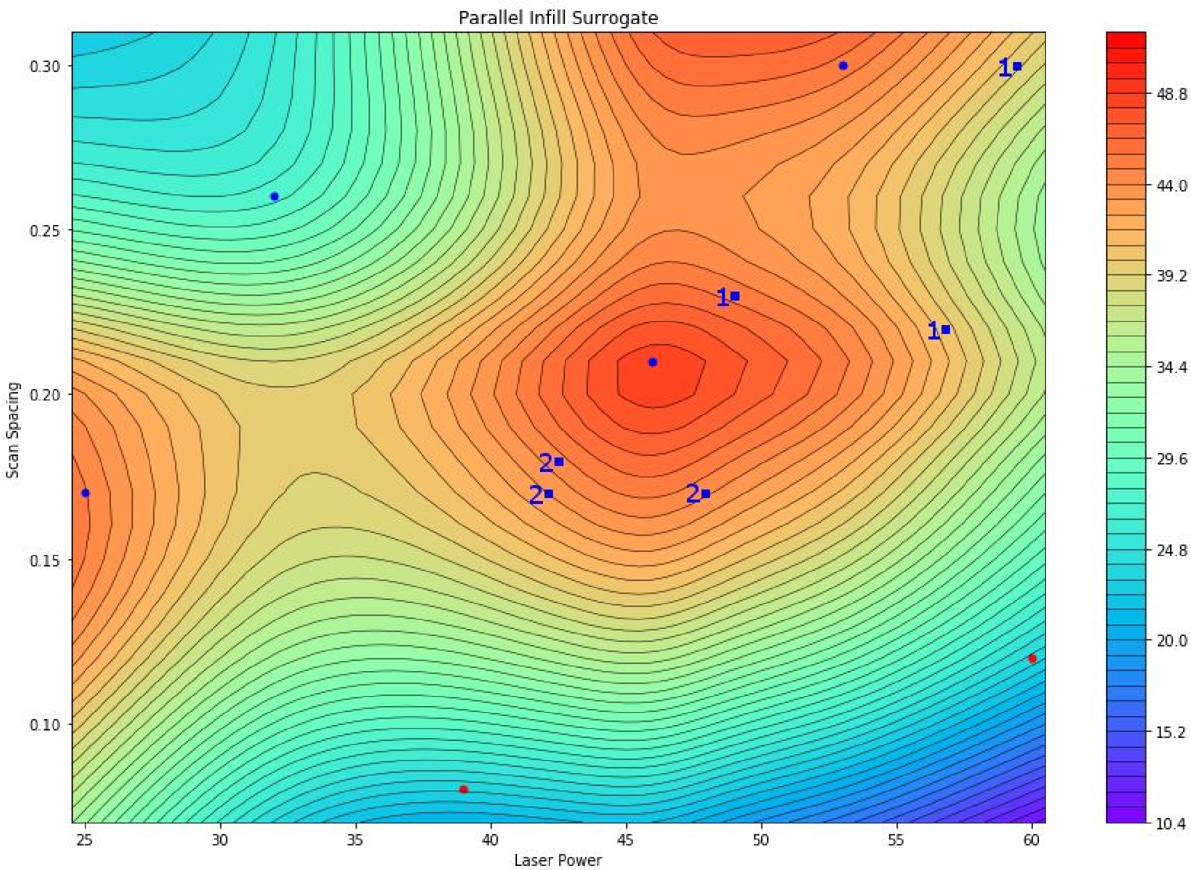
Infill #	Laser Power (W)	Scan Spacing (mm)	Tensile Strength (MPa)
1	60.0	0.25	46.0
2	52.4	0.21	46.4
3	43.8	0.18	45.4
4	48.0	0.22	46.0
5	43.0	0.2	47.6

Table 3. Singular Infill Confirmation Results

The confirmation results show less variation than the experimental results. This leads us to believe that there may be outside factors affecting the experiment.

Experiment #	Laser Power (W)	Scan Spacing (mm)	Tensile Strength (MPa)
1	56.8	0.22	40.4
1	59.4	0.3	39.5
1	49.0	0.23	45.3
2	42.1	0.17	43.2
2	45.2	0.18	44.5
2	47.9	0.17	44.2

Table 4. Parallel Infill Results



●-Feasible Initial Experiment ●-Infeasible Initial Experiment ■-Infill Point

Figure 5. Surrogate constructed after six infill points.

The parallel infill method exhibits similar search behavior. The first experiment explored the top right corner (i.e, high power and scan spacing) and it no longer exhibits the high extrapolation visible in Fig.4.

Experiment #	Laser Power (W)	Scan Spacing (mm)	Tensile Strength (MPa)
1	56.8	0.22	43.0
1	59.4	0.3	50.3
1	49.0	0.23	48.5
2	42.1	0.17	48.9
2	45.2	0.18	46.3
2	47.9	0.17	48.7

Table 5. Parallel Infill Confirmation Results

Discussion and Further Work

In this section, the results of the optimization algorithm as well as improvements that could be made in the future are discussed. After each method was completed, a confirmation test was run on the infill points to examine variation in the previous iterative results. Differences in tensile strength can be observed between both graphs. These differences might be due to the use of recycled powder. We believe more consistent results can be obtained if experiments are done on a larger scale with greater control over other factors.

Both singular and parallel infill methods appear to quickly converge to an area near the center of the graphs (i.e., medium power and scan spacing), which matches operator expectations for parameters that lead to high tensile strength. Both infill methods also produced similar surrogates, but parallel infill methodology was able to achieve this in two days while singular needed five. It must be noted that areas in the surrogate with few or no observations are extrapolations.

While the initial stage has yielded promising results, future improvements can be pursued. Variation in observed results must be accounted for, and existing literature in mathematical optimization propose a variety of methods that may be used. Since mechanical properties are determined by more than two parameters, future experiments should be done to confirm the validity of these methods with more parameters. Additionally, future work can build upon this framework to implement optimization for multiple mechanical properties.

Conclusion

This paper presents an efficient sampling framework for optimizing Selective Laser Sintering process parameters to improve the tensile strength of the printed product. The mechanical properties of the printed parts are important in both manufacturing and prototyping. It is known that a variety of process parameters affect the final product, however the exact relationship is hard to quantify. Physical experiments to determine the optimal process parameters are typically done using factorial design of experiments methods which are both expensive and time consuming. As the number of process parameters tested grows, the number of experiments needed increases exponentially. In this paper two variations of an efficient sampling method to algorithmically determine optimal parameters has been proposed. Both employ a surrogate function to estimate the true relationship between parameters and the target property. The difference between the two variations is the number of experiments per iteration of the algorithm. The first method is based on a single sample update while the second searches for multiple possible samples.

The methods were tested with a Farsoon HT251P machine using (polyamid) PA3300 polymer powder. Laser power and scan spacing were optimised for tensile strength. Not only singular and parallel variations showed similar performance, but also the parallel variation required less time to find the same optimal solution. While the algorithms showed similar optima that matched operator experience, further improvements can be made to account for variation in test results and optimising for multiple mechanical properties.

Acknowledgements

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