Multiobjective Optimization of Laser Milling Parameters of Microcavities for the Manufacturing of DES

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A multiobjective optimization of the laser milling process of microcavities for the manufacturing of drug eluting stents (DES) is presented. The diameter, depth, and volume error are considered to be optimized in function of the process parameters (scanning speed, laser intensity, and pulse frequency). Several experiments are carried out following a design of experiments in a nanosecond pulsed Nd:YAG laser machine on 316 L Stainless Steel as a work material. Two different geometries are studied, and they are considered as another variable for the model. The multiobjective optimization problem is solved by NSGA-II algorithm, and the nondominated Pareto-optimal fronts are obtained. The capability of the process to manufacture within a level of error is also investigated. Relative error capability maps for different scale of features are presented.

Key Words Drug eluting stents; Laser milling; Microcavities manufacturing; Process parameter optimization.

INTRODUCTION

Micromanufacturing processes in the fields of electronics, optoelectronics, micro- and nanomachining, new materials synthesis, and medical and biological applications have become a growing area. Thus, processes capable to manufacture these components with precision, small feature size, and high resolution are needed.

Coronary artery stents were first introduced in the mid-1980s and revolutionized the practice of interventional cardiology. Since then, many significant developments have been introduced, the drug-eluting stents (DES) being the most notable. Many type of DES have been developed during the last years. One of these types is the DES with biodegradable polymer. These stents may offer the antirestenotic benefits of a standard DES, whereas once the polymer has biodegraded, they may offer the benefits of a metallic stent [1]. Some of these DES are metallic stents that include reservoirs where the polymer and the drug are contained, like the Janus stent [2], which incorporates microreservoirs cut into its abluminal side that are loaded with drug.

Laser systems can provide unique solutions in materials processing, offer the ability to manufacture otherwise unattainable devices, and yield cost-effective solutions to complex manufacturing processes [3]. Thus, the use of lasers in materials processing, machining, diagnostics, and medical applications is a rapidly growing area of research.

This article provides a study of the optimization for the laser process parameters selection for the machining of microcavities. These cavities have the dimensions and geometry suitable to be applied in DES fabrication. The laser three-dimensional (3D) milling process of microgeometries is not commonly studied. Moreover, this article adds the novelty of a deep analysis of the dimensional accuracy of the process, presenting its capacities in different scale ranges.

In laser milling technology, the material removal is done by a laser beam through the mechanism of layer by layer ablation. The process is affected by the laser characteristics and the properties of the work material but is mostly influenced by their interaction [4]. The selection of the laser and its parameters significantly affects the dimensional accuracy, the quality, as well as the material removal rate (MRR) of the micropart.

There are many experimental studies dealing with how the laser process parameters affect the quality of the features obtained with laser machining in macro scale. Many authors analyzed the effect of the pulse repetition rate, pulse intensity, and scanning speed on the surface roughness and MRR. Bartolo et al. [5] experimented with tempered steel and aluminum, pointing out that better surface quality is obtained with low average power and pulse repetition rate values. However, the best MRR is obtained with the higher values of both parameters. Cicala et al. [6] machined several metallic materials with a pulsed Nd:YAG laser. Their results pointed out that the MRR is mainly influenced by the pulse frequency. They obtained the lowest levels of surface roughness with low scanning speeds and the highest frequency. Cheng et al. [7] used fs- and ps-lasers on cooper, titanium, and aluminum to study the influence of overlapping, pulse frequency, and number of passes. Saklakoglou and Kasman [8] machined 10 × 10 mm square geometries into tool steel to study the influence of different parameters on maximum milling depth and surface roughness with a 30 W fiber laser machine.
On the micro scale, there are many works investigating the laser machining process in laser microdrilling and laser micromilling. Biswas et al. [9] investigated the influence of pulse intensity, pulse repetition rate, material thickness, and pressure of the gas on the hole tapering diameter and hole circularity at exit of the drilled hole for laser drilling. Kumar et al. [10] investigated the relationship between laser process parameters and groove depth during the notches machining in stainless steel and aluminum. Muhammad et al. [11] studied the basic characteristics of fiber laser cutting of stainless steel 316 L tube and understand the effect of introducing water flow in the tubes on minimizing back wall damages and thermal effect. The influence of laser parameters upon cutting quality for fixed gas type and gas pressure was investigated. Meng et al. [12] designed a fiber laser system for the coronary stent cutting. The effect of different cutting parameters on the kerf width was studied. Karanakis et al. [13] discussed the merits of micromilling using lasers with different pulse durations and wavelengths. They generated 2.5D structures in different industrial materials. Volume removal rates and surface roughness were analyzed presenting good results. Teixidor et al. [14] studied the influence of the key laser parameters on target dimensions and Ra for laser machining of microchannels on steel material. They adopted a multiobjective process optimization to predict the best combination of process parameters.

Many other studies present models and algorithms that predict and optimize the parameters selection. Campanelli et al. [15, 16] implemented an artificial neural network (ANN) and a multiobjective statistical optimization on the laser milling of aluminum 5754. In the first model, they determined the values of the scan speed and the pulse frequency for the preset ablation depth. In the second algorithm, they evaluated the main parameters influence on different responses. Dhara et al. [17] presented an ANN for the optimization of the laser micromachining process where the parameters are selected in order to obtain the groove with the highest depth and the smaller recast layer. Finally, Ciurana et al. [18] developed neural network models and multiobjective particle swarm optimization (MOPSO) for laser ablation of t-shaped features.

In the literature, there is a lack of research for the laser milling of 3D microgeometries. Thus, the objective of this work is to investigate the capability of a nanosecond Nd:YAG laser to produce microcavities with preset dimensions. These cavities have the dimensions and shape to be manufactured into stent struts in order to produce DES. It is necessary to understand the effect of laser milling parameters on the desired dimensional quality. Thus, multiobjective optimization method Non-dominated Sorting Genetic Algorithm (NSGA-II) is adopted to find the optimal set of parameters to improve the dimensional accuracy decreasing the error of the dimensions of the cavities manufactured. Finally, a deeper study has been developed with respect to the errors of the dimensions at different scales in order to understand the process capabilities at error level.

### Multiobjective Optimization Using NSGA-II

Soft-computing techniques, like genetic algorithms (GAs), have contributed to the materials and manufacturing area. GAs are routinely used for materials modeling and design, for optimization of material properties, the method is also useful in organizing the material or device production at the industrial scale [19]. Moreover, it can be used to solve multiobjective optimization problems [20].

In recent times, novel evolutionary data-driven modeling techniques have been proposed. Evolutionary versions of neural networks and genetic programming have been developed. The bi-objective genetic programming (BioGP) approach provides the user to construct models with the right fit. This technique initially minimizes training error through a single-objective optimization procedure, and then a trade-off between complexity and accuracy is worked out through a GA-based bi-objective optimization strategy [21, 22]. GA-based multiobjective neural networks are also utilized for multiobjective optimization complex problems [23].

NSGA-II (modified version of NSGA [24, 25]) is one of the best genetic algorithms for multiobjective optimization. Among all multiobjective genetic algorithms (MoGA), it has been chosen because literature shows that it has been mostly used for the optimization of machining process parameters [26], and it has been demonstrated to be very effective. It has three main features: fast crowded distance estimation procedure, simple crowded comparison operator, and fast nondominated sorting approach [24].

NSGA-II can be roughly described as follows: Firstly, generate a random population (initialize). Then the population is sorted based on nondomination. Once the nondominated sort is complete, the crowding distance value (a measure of density of solutions in the neighborhood) is assigned front wise. Then using simulated binary crossover and polynomial mutation, a descendant population of the same size is generated. The individuals are selected based on crowding distance and rank through a binary tournament selection with a crowded comparison operator. The current generation is combined with the offspring population, and the next generation individuals are set by selection performance. Thereafter, the new parent population is filled by each front until the population size is exceeded.

This work performed multiobjective optimization in laser milling of SS316 L for microcavities manufacturing. A simultaneous consideration of multiple objectives is required. Frequently, the proper process parameters for one response may not be adequate for the other responses. The selection of decision variables for multiple objectives may be in conflict to each other.

To set up the optimization model of machining parameters, the mathematical relationships between machining parameters and optimization objectives should be determined firstly. Since there is no equation that relates them, a second order model is used to set up relations between different responses and process parameters.
These models take the following generic form:

\[
y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \sum_{j=1}^{k} \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \epsilon, \tag{1}
\]

where \(\epsilon\) is the residual error.

Second order models are used to find the optimum values for a response. It includes the second order terms and the interaction terms making it more suitable than linear regressions.

The generic regression form in Eq. (1) is used to develop experimental models for the responses. The following section describes the experiments used to provide data for the optimization process with the different levels of the process variables.

EXPERIMENTAL BACKGROUND

Laser System

The laser system used for the performance of the experiments was a nanosecond Nd:YAG laser Lasertec 40 machine from Deckel Maho. This system is a lamp pumped solid-state laser with 1,064 nm wave length. The laser has an average power of 100 W with a laser beam spot diameter of 30\(\mu\)m, which results in an ideal maximum pulse intensity of 1.4 W/cm\(^2\) (theoretically estimated as [14]). The \(x\) and \(y\) movements are guided by highly dynamic scanner as optical-axis-system with a scanning field of 60\(\times\)60 mm. The machine program itself is generated automatically by the 3D-CAD data by the Lasersoft shape software.

Material

In this work, SS316 L was used as a work material. This was chosen due its common use in coronary stents fabrication.

Milling Experiments

The experiments were performed manufacturing microcavities in two different geometries. The first geometry has a half spherical shape defined by depth and diameter dimensions. The second geometry has a half cylindrical shape with a quarter sphere at both sides, defined by depth, diameter, and length dimensions. The geometries were fabricated with three different combinations of dimensions where the volume is the same. Thus, the experiments are performed in six different geometries. Figure 1 and Tables 1 and 2 present the geometries and the dimensions for the spheres and the cylinders, used in the experiments, respectively. The geometries and dimensions used would allow machining the cavities in cardiovascular stent struts in order to manufacture drug eluting stents.

In the tests, the pulse frequency (PF), pulse intensity (PI), and scanning speed (SS) were considered as input parameters. Preliminary tests were carried out to determine the proper process parameters to be used. From the result, three different levels were selected for each factor, as presented in Table 3. This full factorial design of experiments results in 27 combinations for each geometry studied. Thus, a total of 162 experiments were carried out. All the experiments were machined in the same 316 L SS blank under the same ambient conditions with a track displacement (distance between passes, a) of 10\(\mu\)m. The response variables investigated were the cavity dimensions depth (D) and diameter (\(\Omega\)) and the volume of removed material. Although the cylinder shape has three target dimensions, just two have been modeled, understanding that the results will be similar.

Dimensional measurements and characterization of the laser cut samples was conducted by confocal microscope Axio CSM 700 from Carl Zeiss. Surface replicant silicone was used in order to obtain the negative of some of the samples. 3D scanning electron microscope (SEM) images of these negatives were obtained.

SIMULATION

The experimental data measured is used to develop the second order models in Eq. (1) for responses of the...
relative error of depth, diameter, and volume for the mean values ($\mu$) and the standard deviation ($\sigma$) values. Six equations are obtained where the six responses are correlated with the four process parameters. These constitute the six objective functions for the optimization model, which are considered separately:

$$\text{minimize} \{f(x), g(x), h(x), j(x), k(x), l(x)\}$$

$$\text{s.t. } f(x) \leq b_1, g(x) \leq b_2, h(x) \leq b_3, j(x) \leq b_4,$$

$$k(x) \leq b_5 \text{ and } l(x) \leq b_6 \text{ where } x \in X.$$  \hspace{1cm} (7)

where $f(x)$, $g(x)$, $h(x)$, $j(x)$, $k(x)$, and $l(x)$ represent the objective functions for depth error mean, depth error variance, diameter error mean, depth error variance, volume error, and variance, respectively, with a set of process parameters ($x = x_1 + \ldots + x_n, n = 1, 2, 3, \text{or} 4$) $X$ is the space of solutions.

The four input variables are $x_1 = \text{Geo}$, $x_2 = \text{PI}$, $x_3 = \text{PF}$, $x_4 = \text{SS}$, where Geo is the type of geometry (spherical or cylindrical), PF is the pulse frequency (kHz), SS is the scanning speed (mm/s), and PI is the Pulse Intensity (%).

The objective is to simultaneously minimize objective functions pairs with the above given formulation. To solve this optimization problem, a Pareto-optimal set of non-dominated decision variables approach is considered. The use of a Pareto-optimal set offers better performance than a single combined objective function with weights.

In the laser milling process, the decision variables are constrained within the ranges of the performed experiments (see Table 3).

The NSGA-II simulations were run with a population of 200 individuals and a maximum of 300 iterations. MATLAB R2011b is used to simulate the optimization model. Using NSGA-II algorithm the Pareto frontiers of the nondominated solution sets involving pairs of objectives at a time are obtained as shown in Figs. 2 through 5. The Pareto frontier presents sets of optimal solutions. In the decision variable space, moving from one end of the Pareto front to the other, one objective function is improved, deteriorating the performance of the other objective. However, depending on the shape of the front, both functions may or may not have some relations, as detailed for the following figures.

Figure 2 presents the multiobjective optimization for the relative error diameter for the mean and the variance value. The Pareto frontier is almost a straight line. All the process presents a very good tolerance for the diameter dimension. However, reducing this to 2% increases the relative error for the mean until the 33%. Therefore, better results can be achieved reducing the diameter error mean getting a little bit more of variance.

Figure 3 presents the Pareto frontier of optimal depth and diameter relative errors. Its convex shape shows independence between both relative error parameters. A lower diameter error will turn into worst depth error. However, paying attention to the values at the axes, the range of the diameter is much lower than the one for the depth error. Diameter errors are between 0.27 and 0.274, while the error range for the depth is from 0.32 and 0.4. Therefore, in order to find the best combination of parameters, a good solution would be trying to reduce the depth error, since the diameter error won’t increase much.

Figure 4 shows the Pareto frontier for the optimal volume and diameter relative errors. It is formed by two straight lines, with different inclinations. Small improvements in the diameter further increase the volume. Clearly, increasing the diameter error a bit, the volume error greatly decreases. On the left end of the frontier, the volume and diameter error are around 40% and 27%, respectively, while in the right end, the volume error decreases until 28%, and the diameter error increases until 30%, approximately. Therefore, better results can be achieved reducing the volume error getting a little bit more of diameter error.

Figure 5 presents the Pareto frontier for the volume and the depth relative errors. The concavity shape of the line shows that volume is related to depth parameter.
FIGURE 3.—Pareto frontier of optimal diameter and depth relative error laser parameters.

FIGURE 4.—Pareto frontier of optimal volume and diameter relative error laser parameters.

FIGURE 5.—Pareto frontier of optimal volume and depth relative error laser parameters.
The set of optimal solutions can modify the volume error within a 12% range, while the depth error can be modified from one end to the other of the frontier within an 18% range. Therefore, from the Pareto frontiers in Figs. 4 and 5, reducing the error for depth and diameter dimensions, the volume will get closer to the target.

Figure 6 shows the multiobjective optimization for the three main objective functions as volume, diameter, and depth relative errors. As pointed out in the previous figures, reducing depth relative error is the main objective of the process, concerning the dimension quality. If this error is reduced, the volume error will decrease, and the diameter error will not increase much because the range of all the optimum combinations is lower. Although it can be claimed that there is no combination that reaches an optimal result, a good parameter selection could be a pulse intensity of the 60%, scanning speed of 600 mm/s, and pulse frequency of 45 kHz. This result confirms what was pointed out in a previous study [14]. As pointed out, this combination reduces the depth relative error, keeping the other objective functions in low values.

### Error Analysis

In order to deepen the study of dimensional error that occurs during laser milling, the experimentation was expanded to machining the same geometry but with a magnitude five times bigger. In this case, full factorial experimental design has not been carried out. Six experiments have been performed following the

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**Table 4.** Process parameter combinations for the second set of experiments.

| Trial | PI (%) | PF (kHz) | CS (mm/s) |
|-------|--------|----------|-----------|
| 1     | 60     | 30       | 200       |
| 2     | 60     | 60       | 600       |
| 3     | 78     | 30       | 200       |
| 4     | 78     | 60       | 600       |
| 5     | 100    | 30       | 200       |
| 6     | 100    | 60       | 600       |

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*FIGURE 6.—Pareto frontier of optimal volume, diameter, and depth.*

*FIGURE 7.—Capacity map for the depth dimension (color figure available online).*
combinations of parameters presented in Table 4. This results in a total of 36 more experiments.

As in the previous experiments, the depth and width dimensions were measured, and the relative error was calculated. In this way, capacity maps can be presented. In these maps, the 198 results of the experiments performed fill the space drawing a line which delimits the tolerance which the laser is capable to perform depending on the dimension.

Figures 7 and 8 present the capacity maps for the depth and diameter dimension, respectively. The results on the map are plotted by the geometry. In both cases, the precision of the laser gets better as the dimension increase. As expected, the depth dimension is clearly much more complicated to control than the diameter dimension. The dimensions in the x-y plane are mainly controlled by the movement of the laser, the laser spot size, and the overlapping between the different pulses. Although the spot size varies depending on the process parameters, the other conditions are well controlled. Thus, this results in a good control of the diameter dimensions. On the other hand, for the depth control, the system establishes a constant removing depth for each pulse. This results in a bad approximation because the removed depth for each laser shot changes due to many aspects (thermodynamic equilibrium, process parameters), as is presented in many studies [10, 17].

Besides presenting much larger errors, the results are much more dispersed. Clearly, in dimensions around 50 microns depth, the process becomes poorly controlled. One would expect that in higher dimensions, the results become better, as some results point out (about 0.5 relative error). However, in some conditions, the system moves away completely from the target set. This translates into a much lower tendency than expected, as it happens in the diameter map. Moreover, the results from the cylinder geometry are worst than the spherical ones. It is very evident in the smaller dimension where the sphere results are below 1 and many of the cylinder results are well above that value.

In the case of the diameter dimension, the tendency of the results follows a parabolic shape with very similar values for each dimension. Also, the results for both geometries present are very similar. Hence, as expected, this dimension is much more controlled. Being the spot size known, the error can be reduced. Nevertheless, for micrometric dimensions the errors are between 0.2 and 0.5.
0.5, showing the difficulties in obtaining the preset dimensions.

Clearly, the results presented on a larger scale are better than those obtained in a smaller size. Although the depth is still difficult to control, the forms obtained are much better defined, as presented in Fig. 9. Although the process to obtain the negative of the cavities presents more problems when the dimensions are much smaller, the cavities obtained in the second set of experiments present a shape much similar to the target.

Conclusions

In this study, a multiobjective optimization of the laser milling process of microcavities for the manufacture of DES is presented. The optimization problem is solved by NSGA-II algorithm where the diameter, depth, and volume errors are considered to be optimized function affected by four variables. These variables are the geometry of the cavity, the pulse intensity, the pulse frequency, and the scan speed. The objective is to minimize all three dimensional errors. Experiments in SS316 L are performed to provide data for the model. The capability of the process to manufacture within a level of error is also investigated. Relative error capability maps for different scale of features are presented. Clearly, the process presents more control on the diameter than on the depth dimension. This affects the volume error. There are some trends and specific conclusions.

1. Multiobjective NSGA-II provides resourceful and efficient means to the decision maker of laser milling process parameters.
2. The nanosecond Nd:YAG laser is capable to produce microcavities with preset dimensions presenting relative error around 1.5 for the depth dimension and 0.3 for the diameter dimension.
3. The capability of the laser milling process to produce microgeometries is limited by the scale of the feature. The bigger the dimensions of the cavity, the smaller the dimensional error.
4. The diameter dimension error decreases more than the depth error when the scale of the cavity machined is increased.
5. The geometry of the feature to machine affects the process performance.
6. A good parameter selection is presented for the laser milling of microcavities; pulse intensity of the 60%, scanning speed of 600 mm/s, and pulse frequency of 45 kHz.

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