Multi-objective optimization of laser milling parameters of micro-cavities for the manufacturing of DES

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Abstract

This paper presents a multi-objective optimization of the laser milling process of micro-cavities for the manufacturing of drug eluting stents (DES). The diameter, depth and volume error are considered to be optimized in function of the process parameters including laser intensity, pulse frequency and scanning speed. A set of designed experiments is carried out in a pulsed Nd:YAG laser system using 316L Stainless Steel as a work material. Two different geometries are studied, and they are considered as another variable for the model. The multi-objective optimization problem is solved by NSGA-II algorithm, and the non-dominated 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.

Introduction

Micro-manufacturing processes in the fields of electronics, optoelectronics, micro- and nanomachining, new materials synthesis, and medical and biological applications have become a growing area. This creates the need to find processes to manufacture these components with better precision, higher resolution, smaller feature size, true 3D fabrication, and higher piece part fabrication throughput.

Coronary artery stents revolutionized the practice of interventional cardiology after they were first introduced in the mid-1980s. Since then, there have been significant developments in their design, the most notable of which has been the introduction of drug-eluting stents (DES). During the last years many type of DES have been developed. One of these types is the DES with biodegradable polymer. Interest has focused on these stents because initially after implantation, they theoretically may offer the antirestenotic benefits of a standard DES, whereas once the polymer has biodegraded, they speculatively may offer the safety 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 micro-reservoirs 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.

In laser milling technology the material is removed by a laser beam through the layer by layer ablation mechanism. The removal of material during laser milling is affected by the characteristics of the laser beam and the workpiece but is mainly determined by the way that both interact [4]. The key process parameters which can be controlled and modified in order to obtain optimal machining results are the pulse frequency, the pulse intensity, and the scanning speed. The selection of the laser and its parameters significantly affects the quality of the micro-feature created and also the material removal rate.

There are several experimental research works which deal with the effect of the laser process parameters on the quality of the final parts of laser machining in macro scale. Many authors analyzed the influence of the pulse frequency, scanning speed and pulse intensity on the surface roughness and material removal rate. Bartolo et al. [5] experimented with tempered steel and aluminum pointing out that better surface quality is achieved with low pulse frequencies and laser power are used. However, the higher material removal rate is achieved increasing both parameters. Cicala et al. [6] used an Nd:YAG pulsed laser for machining of aluminum alloy, stainless steel and titanium materials. Their results showed that the material removal rate depends mainly on the frequency of the laser pulses. They obtained the lowest levels of surface roughness with low scanning speeds and the highest frequency. Cheng et al. [7] used a femtosecond and picoseconds lasers on cooper, aluminum and titanium alloys to study the effects of pulse overlap, repetition rate and number of overscan. Saklakoglou and Kasman [8] machined 10x10mm square geometries into tool steel to study the effect of different process parameters on surface roughness and maximum milling depth using 30W fiber laser machine.

In the micro scale there are many works investigating the laser machining process in laser microdrilling (Biswas / Kumar) and laser micro-cutting (Muhammad / Meng), there are few researches about laser 3D micromilling. Biswas et al. [9] studied the influence of lamp current, pulse frequency, air pressure and thickness of the job on the hole circulatity at exit and the hole taper of the drilled hole for laser drilling of gamma-titanium-aluminide. Kumar et al.[10] investigated the dependence of groove depth on laser power, repetition rate, number of scans and gas pressure in the generation of micro-notches in stainless steel and aluminium. Muhammad et al. [11] investigate the basic characteristics of fiber laser cutting of stainless steel 316L 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 cardiovascular stent cutting system based on fiber laser where the kerf width size was studied for different cutting parameters including laser output power, pulse length, repeat frequency, cutting speed and assisting gas pressure. Karanakis et al. [13] discussed the merits of laser 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 effect of the key laser parameters on target dimensions and surface roughness for laser milling of micro-channels on tool steel. They adopted a multi-objective process optimization to predict the best combination of process parameters.

Many other research works developed models and methods to simulate the process and predict the best set of parameters for the final result. Campanelli et al. [15, 16] implemented an Artificial Neural Network and a multi objective statistical optimization on the laser milling of aluminium 5754 using a Nd:YAG laser. In the first model they determined the values of the scan speed and the repetition rate for the preset ablation depth. In the second algorithm they evaluated the influence of the main parameters on the depth, MRR and surface roughness. Dhara et al. [17] developed a strategy for predicting the optimum machining parameter setting for the generation of the maximum depth of groove with minimum height of recast layer. Finally, Ciurana et al. [18] developed neural network models and multi-objective particle swarm optimization (PSO) of process parameters for laser ablation of t-shaped features.

There is a lack of research in the literature for the laser milling of 3D micro-geometries. Therefore, the objective of this work is to study the capability of a nanosecond Nd:YAG laser to produce micro-cavities 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 capture the influence of laser milling process parameters on the desired dimensional quality. Thus, multi-objective optimization (NSGA-II) method is adopted to find the optimal set of parameters to improve the dimensional accuracy reducing the error of the dimensions of the cavities manufactured. Finally, a deeper analysis has been carried out with respect to the errors of the dimensions at different scales in order to understand the capabilities of the process at error level.

2. Multi-Objective Optimization using NSGA-II

Multi-objective optimization problems can be solved by using evolutionary computational algorithms such as genetic algorithms [19]. NSGA-II (Non-dominated Sorting Genetic Algorithm, modified version of NSGA [20, 21]), is one of the most popular multi objective optimization algorithms with three special characteristics; fast non-dominated sorting approach, fast crowded distance estimation procedure and simple crowded comparison operator [20]. It has been most widely applied for optimizing machining process parameters and recognized as one of the best evolutionary algorithms for multi-objective optimization [22].

Generally, NSGA-II can be roughly detailed as follows: Once the population is initialized the population is sorted based on non-domination into each front. Once the sorting is complete, the crowding distance value is assign front wise. The individuals in population are selected based on rank and crowding distance. The crowding distance is a measure of how close an individual is to its neighbours. Large average crowding distance will result in better diversity in the population. Parents are selected from the population by using binary crossover and polynomial mutation based on the rank and crowding distance. Offspring population and current generation population are combined and the individuals of the next generation are set by selection. The new generation is filled by each front subsequently until the population size exceeds the current population size. The selection is based on rank and the on crowding distance on the last front.

This work conducted multi-criteria optimization to investigate the dimensional accuracy in laser milling of 316L stainless steel for micro-cavities fabrication. Optimal selection of process parameters of laser milling can be formulated and solved as an optimization problem. A simultaneous consideration of multiple objectives is required. Usually, process parameters selected for one objective function may not be suitable for the other objective function presenting conflicting objectives. This presents a challenge for the optimization problem, since selection of the parameter settings (decision variables) for given multiple choices which 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 establish input-output relationship between response and process parameters efficiently. These models take the following generic form:

$$y = \beta_o + \sum^k \beta\ x + \sum^k \beta_i\, x\, x_i + \sum^k \beta\ x^2 + \qquad (1)$$

where is the residual error.

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

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

3. Experimental background

3.1 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 1,064nm wave length. The laser has 100W average laser power and with a laser beam spot diameter of 30 µm, which results in an ideal maximum pulse intensity of 1.4 W/cm2 (theoretically estimated as [14]). The x and y movements are guided by highly dynamic scanner as optical-axis-system with a scanning field of 60x60 mm. The machine program itself is generated automatically by the 3D-CAD data by the Lasersoft shape software

3.2 Material

In this work 316L Stainless steel was used as a workpiece material test. This material was selected because it is commonly used for coronary stents fabrication.

3.3 Milling experiments

The experiments were carried out machining micro cavities 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 Table 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.

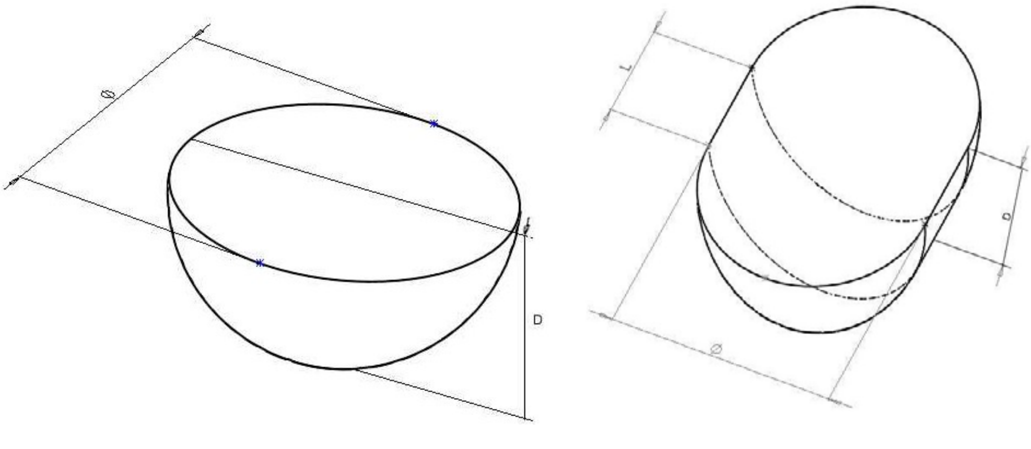


Figure 1. Cavity geometries used in the experiments.

Table 1. Sphere geometry dimensions.

Geometry	Depth (µm)	Ø (µm)	Volume (µm^3)
Sphere 1 (e1)	50	166	721414
Sphere 2 (e2)	70	140	718377
Sphere 3 (e3)	90	124	724576

Table 2. Cylinder geometry dimensions.

Geometry	Depth (µm)	Ø (µm)	Length (µm)	Volume (µm^3)
Cylinder 1 (c1)	50	130	55	723220
Cylinder 2 (c2)	70	110	46	721676
Cylinder 3 (c3)	90	100	36	725707

In the experiments, the scanning speed (SS), the pulse frequency (PF) and pulse intensity levels (PI) were considered as input parameters. A full factorial design was used. A preliminary test was carried out to determine the proper process parameters to be used. From the result, three different levels were selected for each factor, as is presented in Table 3. These design of experiments results in a total of 27 unique factor level combination for each geometry studied. Thus, a total of 162 experiments were carried out. All the experiments were machined in the same 316L SS blank under the same ambient conditions with a track displacement (distance between passes, a) of 10µm. The response variables investigated were the cavity dimensions depth (D) and diameter (Ø) 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 for was used in order to obtain the negative of some of the samples. 3D SEM images of these negatives were obtained.

Table 3. Factors and factor levels.

Factors	Factor Levels		
Scanning Speed (SS) [mm/s]	200	400	600
Pulse Intensity (PI) [%]	60	78	100
Pulse Frequency (PF) [kHz]	30	45	60

4. Simulation

The experimental data measured is used to develop the second order models using the generic form in Eq (1) for responses of the relative error of depth, diameter and volume for the mean values (μ) and the standard deviation (σ) values. Six equations are obtained where the six responses are related with the four controllable process variables including the interaction terms and the second order terms. These constitute the six objective functions for the optimization model, which are considered separately.

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

$$\text{s.t.}\quad f(x) \le b\ ,\ g(x) \le b_2, h(x) \le b_3, j(x) \le b_4, k(x) \le b_5 \text{ and } l(x) \le b_6 \quad \text{where } x \in X.$$

(7)

In the optimization problem formulation in Eq. (7) $f(x)$, $g(x)$, $h(x)$, $j(x)$, $k(x)$ 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 ($x = x\ + \cdots + x_n,\ \ n = 1, 2, 3 \text{ or } 4$). X is the solution space with all feasible values for the process parameters.

The four controllable process variables are x1=Geo , x2=PI, x3=PF, x4=SS, where Geo is the type of geometry (spherical or cylindrical), PI is the Pulse Intensity (%), PF is the pulse frequency (kHz) and SS is the scanning speed (mm/s).

In the above given formulation, the objective is to simultaneously minimize the objective functions. In solving this optimization problem, a general approach based on Pareto-optimal set of non-dominated decision variables settings is considered. The selection of a Pareto-optimal set avoids the problem of a single combined objective function with weights which often leads to a unique solution but offers no other solution to the decision maker for optimum parameter selection.

In the case of laser machining process, the optimization problem is defined with multiple objectives. Decision variables such as geometry (Geo) scanning speed (SS), pulse intensity (PI), and pulse frequency (PF) are constrained within the ranges of the experiments (see Table 3).

The simulations were run by using a population of 200 individuals and a maximum number of 300 iterations. After obtaining the best individuals values in each iteration of the simulation, the individuals are plotted in a two-dimensional objective space for viewing. This procedure is repeated until a clear Pareto frontier forms. Matlab R2011b is used to simulate the optimization model. The Pareto frontiers of the non-dominated solution sets are obtained by using multi-objective NSGA-II method as shown in Figure 2 through Figure 5.

Figure 2 presents the multi-objective 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.

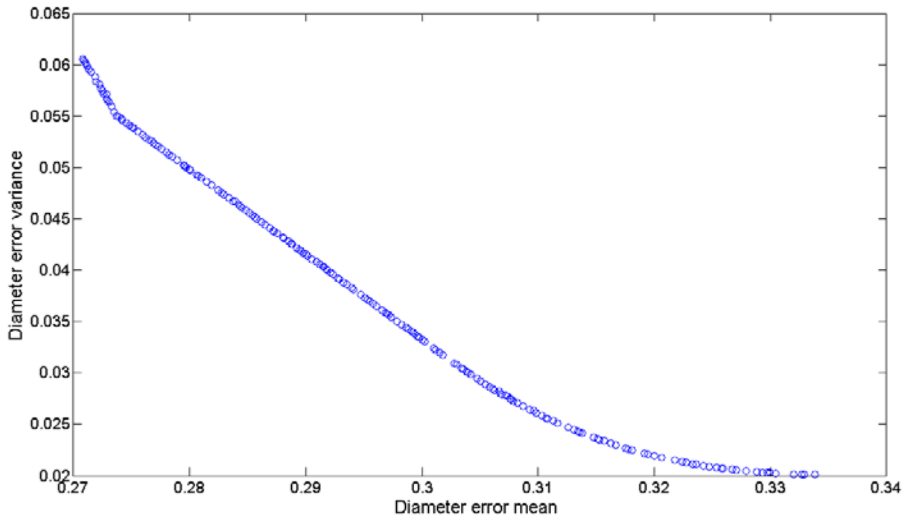


Figure 2. Pareto frontier of optimal diameter mean and diameter variance relative error laser parameters.

Figure 3 presents the multi-objective optimization for the depth and diameter relative errors. The convexity shape of the Pareto frontier shows a clear independence between both error objective parameters. A lower diameter error will result in a higher depth dimensional 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, would be a good solution trying to reduce the depth error, since the diameter error won't increase much.

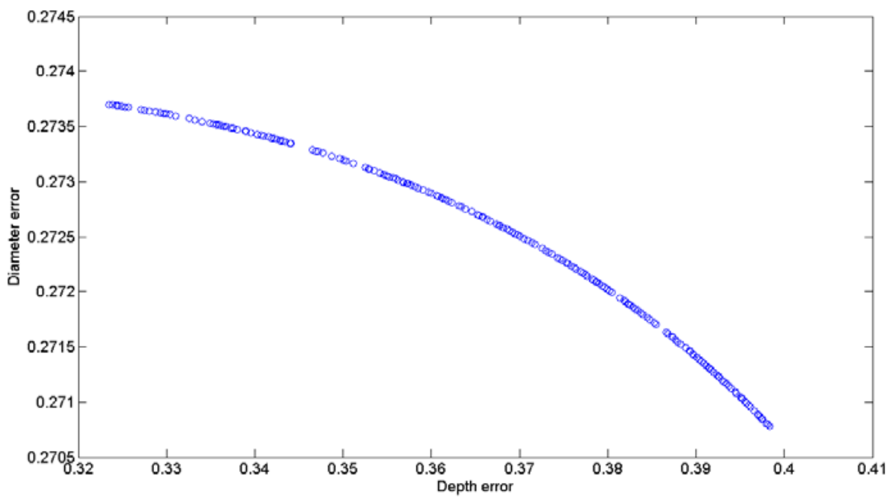


Figure 3. Pareto frontier of optimal diameter and depth relative error laser parameters.

Figure 4 and 5 show the pareto frontier for the volume with the diameter and the depth relative errors, respectively. The concavity shape of both lines shows that volume is related to both parameters. Therefore, as expected, reducing the error for depth and diameter dimensions, the volume will get closer to the target. In the Figure 4, the pareto frontier is formed by two straight lines, with different inclinations. Small improvements in the diameter increases further the volume.

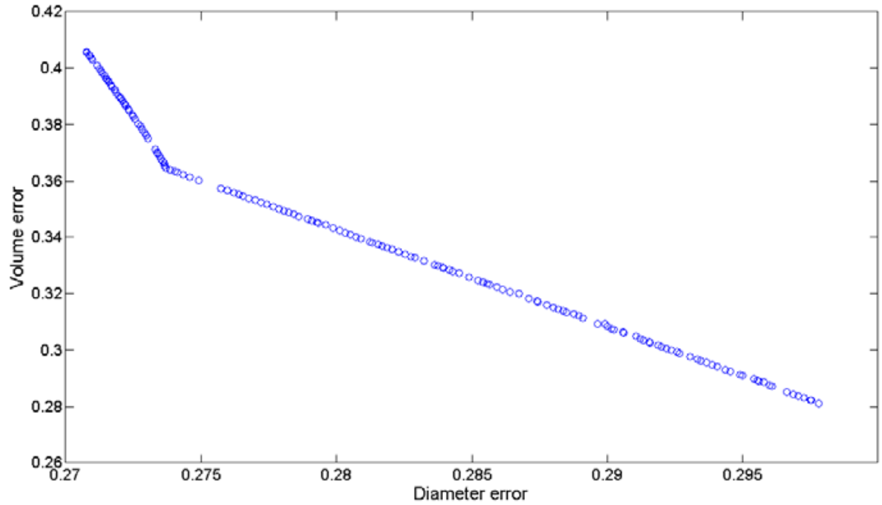


Figure 4. Pareto frontier of optimal volume and diameter relative error laser parameters

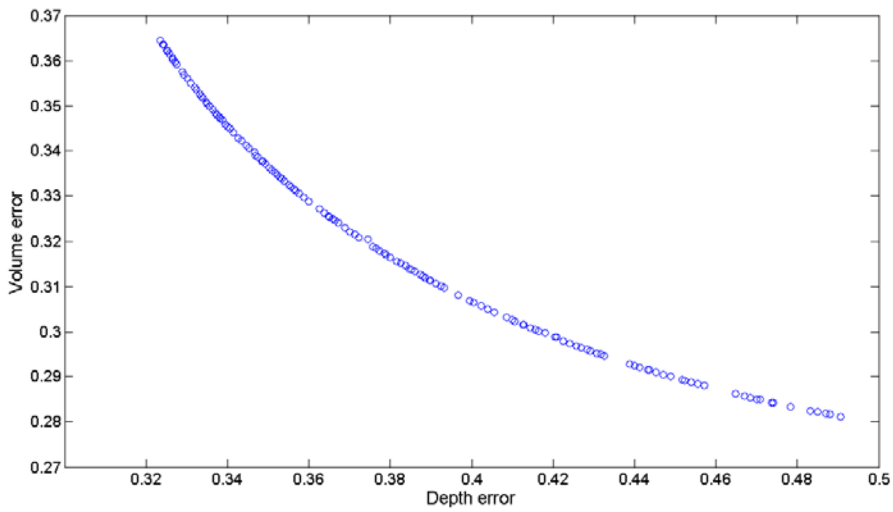


Figure 5. Pareto frontier of optimal volume and depth relative error laser parameters

Figure 6 shows the multi-objective optimization for the three main objective functions as volume, diameter and depth relative errors. As pointed out 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 not combination that reaches an optimal result, a good parameter selection could be a pulse intensity of the 60%, pulse frequency of 45 kHz and scanning speed of 600mm/s.

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.

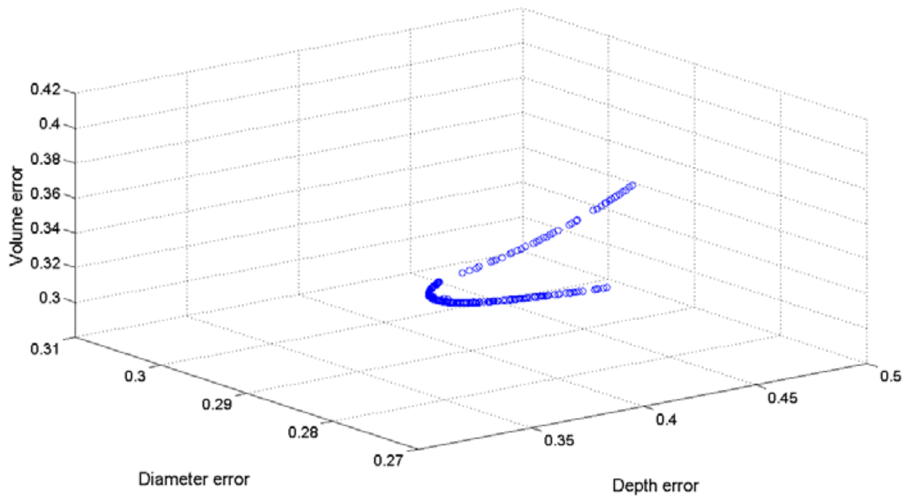


Figure 6. Multi-objective optimization for volume, diameter and depth relative error laser parameters

5. 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 combinations of parameters presented in Table 4. This results in a total of 36 more experiments.

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

As in the previous experiments the depth and width dimensions were measured, as well as 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 performance depending on the dimension.

Figure 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. 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.

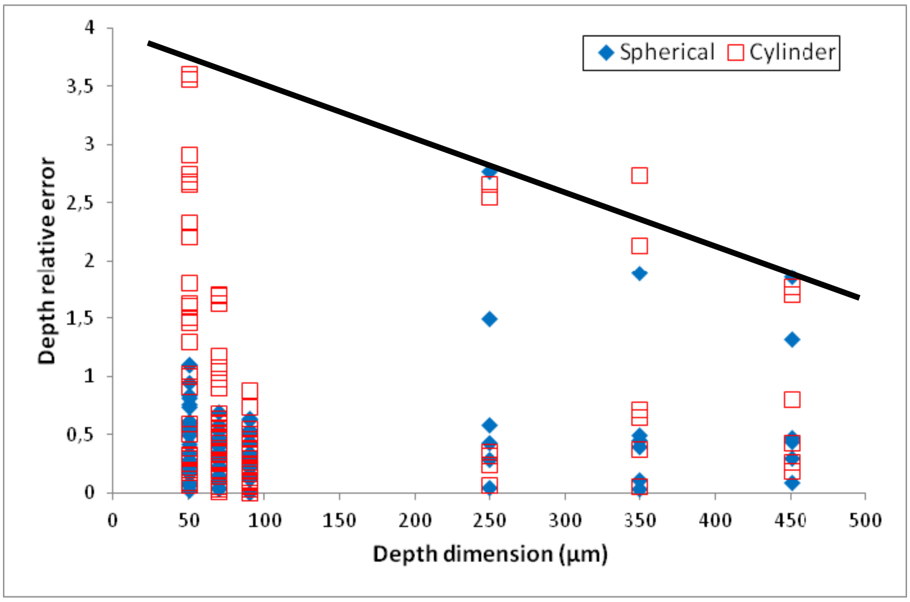


Figure 7. Capacity map for the depth dimension.

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 showing the difficulties in obtaining the preset dimensions.

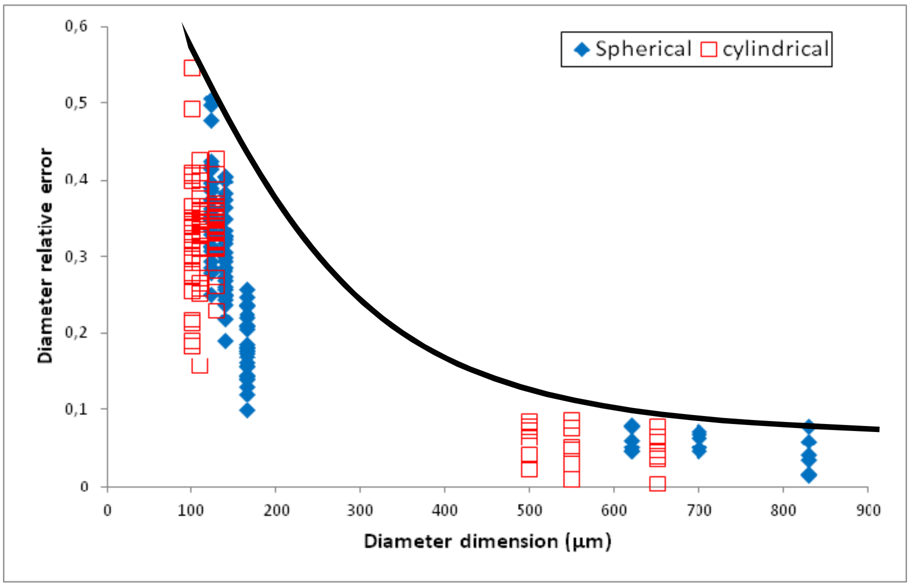
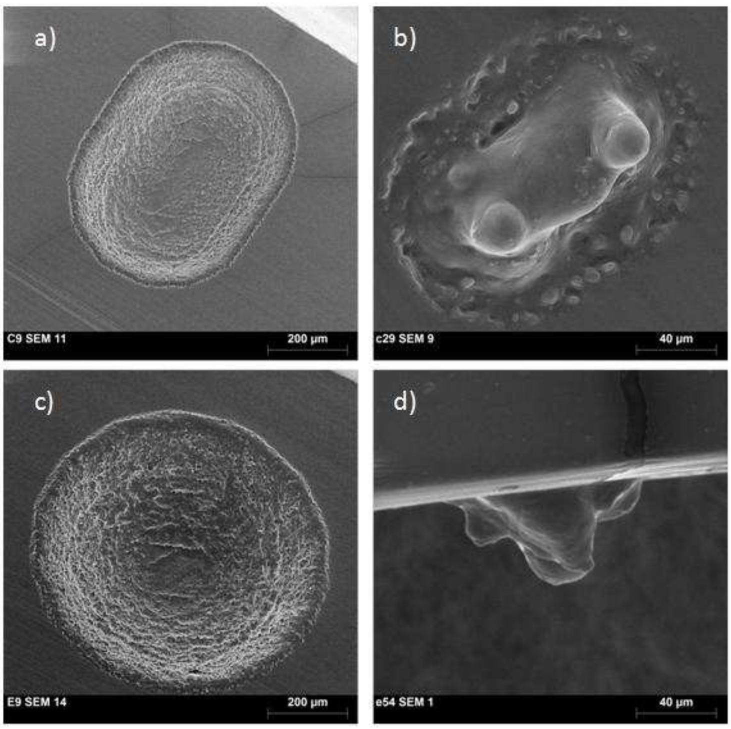


Figure 8. Capacity map for the diameter dimension.

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 Table 5. Although the process to obtain the negative of the cavities present more problems when the dimensions are much smaller, the cavities obtained in the second set of experiments present shape much similar to the target.

table 5. SEM images of cavities negative; a) geometry C1; PI = 60%, PF = 60 kHz and SS = 600mm/s, b) geometry c2; PI = 60%, PF = 30 kHz and SS = 200mm/s, c) geometry E1; PI = 60%, PF = 60 kHz and SS = 600mm/s, d) geometry e2; PI = 100%, PF = 60 kHz and SS = 600mm/s.



6. Conclusions

In this study a multi-objective optimization of the laser milling process of micro-cavities for the manufacture of drug eluting stents 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 repetition rate and the scanning speed. The objective is to minimize all three dimensional errors. Experiments in 316L Stainless Steel are carried out 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. Some trends and specific conclusions can be drawn as following:

1. Multi-objective NSGA-II provides Pareto frontiers of non-dominated solution sets for optimum laser milling process parameters, providing a resourceful and efficient means to the decision maker.
2. The nanosecond Nd:YAG laser is capable to produce micro-cavities 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 micro-geometries is limited by the scale of the feature. As bigger the dimensions of the cavity, 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. Although laser milling is a complex process and it is not easy to find the proper combination of process parameters to achieve the final part, a good parameter selection is presented for the laser milling of micro-cavities; pulse intensity of the 60%, pulse frequency of 45 kHz and scanning speed of 600mm/s.

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